International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-1, November 2019

A Brain Computer Interface–Based P300 Speller for Home Appliances Control System

Praveen Shukla, R. K. Chaurasiya, Shrish Verma

Abstract*: Enviourment control is one of the critical difficulties for handicapped individuals who experience the ill effects of neuromuscular ailments. Brain computer interface systems empower a subject to communicate with a PC machine without drawing down any solid action. This communication does not depend in light of any ordinary medium of correspondences like physical developments, talking, and motion and so forth. The most vital desire for a home control application is high accuracy and solid control. In this study, row column–based (2 Row, 3 columns) P300 paradigm for home appliances control was designed. In this article we analyse a real time EEG data for P300 speller using support vector machine and artificial neural network for high accuracy. Using this proposed method we are able to find the target appliance in a correct and fastest way. Four healthy subjects were participating in this study. Artificial neural network gives 85% accuracy within 10 flashes. The results shows this paradigm can be used for select option of a home appliances control application for healthy subjects with user convenient and reliable.

***Keywords:* Brain computer interface, P300 signal, Classification, Home appliances**

I. INTRODUCTION

Brain Computer Interface (BCI) is a brief human-to-computer correspondence based entirely on the decoding of electroencephalographic (EEG) responses produced by a subject's stimuli. BCI systems enable a subject to interact with a PC device without any solid action being drawn down. This communication does not rely on normal correspondence, such as physical advances, voice and movement, etc. Controlling and connecting with the living condition is one of the fundamental needs of individuals in day by day life. BCI gives a medium of correspondence to profoundly suffering patient like amyotrophic lateral sclerosis (ALS), brain stroke and other neurological problems. Through BCI system these disable people can control devices by the brain activity. BCI –based appliances control system gives an opportunity to control TV/mobile-phone/door/fan/light-bulb/electric-heater by themselves.

Revised Manuscript Received on November 30, 2019.
***** Correspondence Author
Praveen Shukla*, Dept. of Electronics & Communication**,** National Institute of Technology, Raipur India. (pkshukla.phd2017.elx@nitrr.ac.in)
R.K.Chaurasiya, Dept. of Electronics & Communication, Malaviya National Institute of technology, Jaipur India. (rkchaurasiya.39@gmail.com)
Shrish Verma, Dept. of Electronics & Communication, National Institute of Technology, Raipur India (shrishverma@nitrr.ac.in)

This manipulate functionality would possibly ensure to reduce dependence on caregivers, and improves lifestyles for human beings with neuromuscular diseases.
It is import to theses system classification accuracy should be high, so that classify signal convert into command signal and device will activate into desire time. P300 speller is one of BCI's most common uses that work on the odd-ball paradigm principal. A system of spellers obsessed with the P300 ERP is mostly called a P300 speller. P300 infers a positive going ERP conveyed after 300 ms of prompting. Sutton recorded the first P300 ERP in 1965. In the event that a subject is inquired to recognize between two stimuli (displayed in an arbitrary arrange), wherever one amongst them rarely occur (the "odd-ball"), then after 300ms the P300 wave is generated and this phenomenon is known as "odd-ball paradigms". The first P300-based row column speller was created by Farwell & Donchin, 1988 [1]. The size was English speller 6 ×6 matrix of latter. All six rows and six column of the matrix were highlighted in random order while the subject was asked to concentrate on the specific character. Presence of P300 ERP in order to detect of target character through multi –trail approach is a common practice.
he first speller additionally referred as Row-column (RC-primarily based) speller [2]. Later on row column–based paradigm English alphabet and number replace dummy faces and pictures [3, 4]. There are various other paradigms single character (SC) paradigm [5], which can spell only one character at a time, check Board (CB) paradigm [6], rapid serial visual presentation [7], Hex-o-Spell [8], cake speller [9] etc. Some limited research BCI–based P300 Speller home appliances control system like row column-based speller (RC) [10, 11], and region based paradigm [12], Hoffman approach have been already implemented. Some researchers gave an idea about single and multiple appliances control through different approaches like Bluetooth, arduino, infrared, web server, and microcontroller, for light [13], door [14], fan [15], music [16], buzzer [17] air conditioner [18], and multiple (fan, tv, blub, door etc.). In this paper, we designed a P300–based BCI home appliances control system. We used appliances in the place of number and dummy faces. In this article we detect a P300 ERP signal for high classification and detect a correct target appliance using a Support vector Machine (SVM) and artificial neural network (ANN) classification methodology. The remaining of the paper is divided into the following section: Section II proposed BCI-based P300 paradigms for home appliances control system Section, III describes dataset and experimental analysis,

Section IV shows experimental results, Section V describes discussion and finally concludes the paper.

II. PROPOSED BCI –BASED P300 PARADIGM FOR HOME APPLIANCES CONTROL SYSTEM

In this paper, single channel–based (Neurosky mind wave mobile headset) multiple appliances control system was designed. A BCI–based P300 Speller for home appliances control system consists of several stages data collection, pre-processing, extract features, classification and control translation. Correct classification is a main task for EEG –based home appliances control system. Once signal classified and converted into control signal appliances will activate.The proposed block diagram for home appliances control system is depicted below in Figure 1.

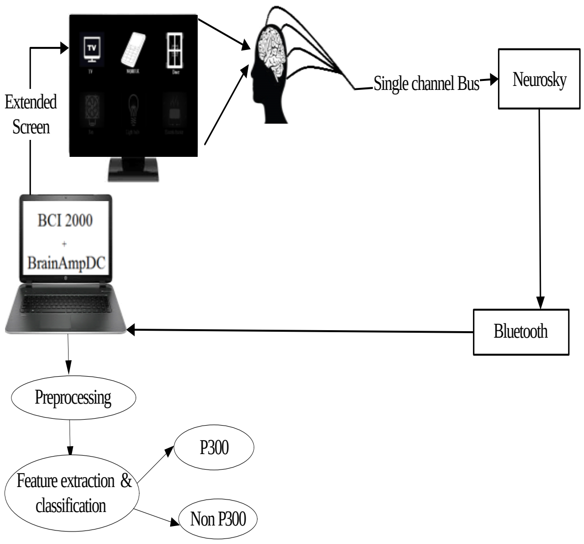

Figure 1. Block representation of P300 speller for BCI-based home appliances control system.

There are many challenges factor of practical implementation of P300 speller 1) User convenient 2) High accuracy 3) System reliability. In this article we have attempted to tackle the above challenging P300 spell-related factor. We have used support vector machine and artificial neural network classification algorithms to detect target appliance accurately respectively less number of trails. We took decimated and filtered amplitude EEG signal have been taken as a feature coefficient for classification. The method of decimation transforms high-dimensional information into a feature vector of lower dimensions. This reduced feature vector as a result, required lesser size of training and provides high classification bit rate and classification accuracy.

III. DATA SET FOR EXPERIMENTAL ANALYSIS

The subjects are healthy and age range between 25-35. The dataset was collected NeuroSky mind wave–mobile headset. It contains single dry sensor that can be situated on the forehead and three other dry sensors on left ear for references. It includes a microchip which tactics EEG signals and exchanges the information via Bluetooth. The NeuroSky Mind Wave has a wearable gadget for viewing the electrical signs created by neural development in the cerebrum. The gadget is involved eight primary parts; adaptable ear arm, ear cut, battery territory, control switch, customizable head band, sensor tip, sensor arm and inside think equip chipset. In the proposed main menu, row column-based P300 paradigm consists of appliances (icons), TV, mobile, door, fan, light bulb and electric heater. In RC–based paradigm the row and column flashes randomly, subject was asked to focus on the particular appliance that he want to pick. Main menu has 2 rows and 3 columns are depicted in Figure.2

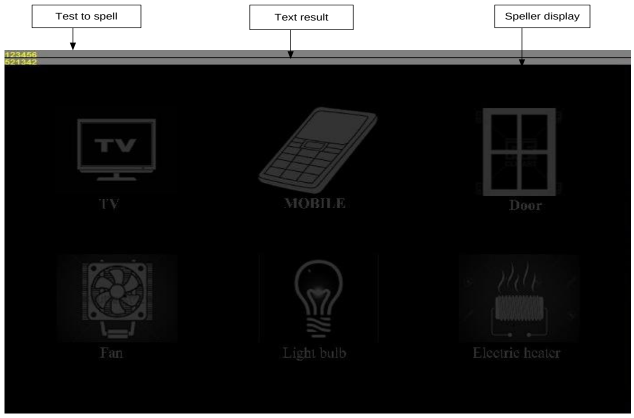

Figure 2. Main menu of the architecture Proposed method

Once matrix finishes flickering, selected command is performed, user can access specific submenu. All appliances have specific submenu, user can select particular submenu according to his needs. Subjects were asked to complete 20 selections. Figure.3 shows light submenu size of 2×3 matrix. Only one row and column can contain the target appliance in flashing of 5 different rows and columns, with the flashing equal to 2/5=0.4. The EEG signals recorded for four subjects in three sessions (Session 1, Session 2, and Session 3). Each session divided into number of runs. In every run row and column was intensified 100ms followed by 80ms dark time. The block randomization set was 5. 2 out of 5 such intensification contains target appliance. For each target appliance, the random row and column method was repeated 10 times. Session 1 and session 2 was the training session, and session 3 was testing session. In session 1 and session 2 was training session real time EEG signals at sampling rate 512 row column intensification and class level were provided and in testing session class level were not provided. The subject task was predicted to target appliance for each run of session 3.

Figure 3. Submenu of light device

Retrieval Number A4606119119/2019©BEIESP
DOI: 10.35940/ijitee.A4606.119119
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering & Sciences Publication

IV. PROPOSED METHODS

There are two tasks, first one detect the P300 ERP and second identify target appliance. For each block of intensification 5 row and column we have to identify target appliance. For detecting P300 ERP component and identify target appliance, we have trained support vector machine and artificial neural network classification algorithms. Data was acquired in real time because of background brain activity noises are included. It is very difficult to get target appliance in single trails approach. We have applied multi trail approach for detecting target appliance. For correct appliance detection we are applying these steps which are following.

A. Pre-processing and feature extraction:

When the subject is available for the uncommon or amazing assignment, P300 signals are evoked after 300 ms, these signals are generated as a consequence of odd–ball paradigms in which the subject is asked to select a random sequence of stimuli. For detecting P300 ERP we fixed time windows signals 0 ms to 600ms which is large enough to collect response correctly. As we recorded data samples rate 512 Hz, 0-600 ms posterior gives 300 samples. After that we introduced a Type 1 filter with cut-off frequency of 8 order Chebyshev 0.1 to 30 Hz.

Due to decimation sample size was reduced 50 times (512/30). Hence sample size was 300/17 = 17 samples. Then we applied signal normalization to the interval [-1, 1].Thus for a single appliance, feature vector is 75 (5 intensification × 15 trails) size of 17×1. Out of 75, 30 are belongs to class +1, and remaining are 45 are belongs to class -1. We have used all main and submenu appliance icon all the run of session 1 and session 2 to prepare training set of subject 1, 2, 3 and subject 4. There are 10 tasks were selected (20 selection for both levels) in session 1 and session 2. For training session feature vectors is 20×75 = 1,500 in the size of 17×1. Out of 1,500 features vectors 600 are belong to class +1 and remaining 900 are class -1. We collected data for 20 selection as well as testing session.

Figure 4. Shows P300 ERP signals in blue colour (class +1) of raw data (300 samples) and Non –ERP signals in red colour (class-1). Figure 5. Shows plot of all average value of the class +1 and class-1 signal of run 1 of session 1. Blue line shows P300 ERP of class +1 and red line shows non P300 ERP of class-1.

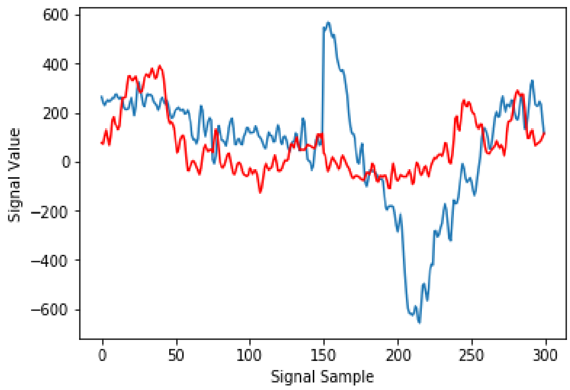

Figure 4. Sample variation with P300 ERP in Blue colour

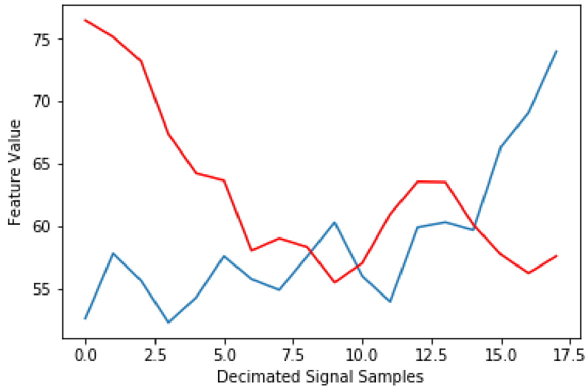

Figure 5. Plot of decimated signal sample verses features

B. Classification

SVM and ANN classifier has been used for P300-based home appliance control system.

(1) Support Vector machine:

SVM classifier gives good gernalization capbility. For liner separate data SVM classify in two hyperplane in such a way separation margin between the dataset of two classes is maximized. For non linearly seperable data points, the task involve the maximizing seperation margion and controlling error pointcalled stack variables which are allowed in the process.This problem called as a optimzation problem and solved by langraze's theorem. As resultant we found a linear discrete function for novel data points x as equation (1).

$$\mathbf{F(x)} = \sum_{i=0}^{n} y_i \, \lambda_i(x.x_i) + \mathbf{b} \qquad (1)$$

Where x_i ,i=1,2......N are trainning data points with $y_i \in \{-1,1\}$, $i = 1,2 \ldots N$, λ_i i=1,2....N.

It is shown that replacing dotproduct $(x.x_i)$ by a Kernal function K $(x.x_i)$. In this praposed work we have applied Radial Basis Function (RBF) to classify the data

$$\mathrm{K}\,(x.x_i) = \exp\left(-\frac{||x-x_i||^2}{2\sigma^2}\right) \qquad (2)$$

(2) Artifical Neural Network :

In this EEG-based home control system dataset, proposed multilayer feed-forward with three hidden layers with sigmoid function was used for classification. The resilient back propagation method was used for the training purpose. As no thumb rule exited for the architecture of multilayer perceptron (MLP). So this presented work three hidden layer (first layer consisted 256 neurons and second layer consisted 5 neurons and third layers consisted 2 neurons based on mean square error) was selected trial and error basis. In this praposed work we have train for both the subjects full trainning datset 1,500 feature vectors (i.e. 600 (class +1) and 900 (class -1)) feature vector using 5-fold cross validation technique. Because data was too noisy so it can't detect correct character in single trails. We applied multi trail approach using of both ANN and SVM classifier in test dataset and classified desire contain of target appliance.

V. RESULTS

In this study accuracy was predicted into two ways. The first one is to determine total 20 selection prediction. Second one is to determine correct appliance selection respect to level wise. Total target selection accuracy for first flashes using ANN classifier is 60% to 65%. 85% average accuracy achieved using ANN classifier for main menu and submenu in 10 trails. SVM classifier gives total target selection accuracy for first flashes 55% to 60 %. SVM gives 82 % average accuracy achieved in just 10 trails. ANN classifier gives better result than SVM. Target appliance prediction accuracy in respect to menus using ANN classifier achieved 85.4%.

Table 1. Total target prediction and main and sub menu level wise accuracy in percentage using SVM and ANN classifier.

No.of flashes	Main men (ANN)	Sub menu (ANN)	Main menu (SVM)	Sub menu (SVM)	Total target prediction
1	65	62	60	59	65
2	70	72	65	68	70
3	78	74	75	74	75
4	79	75	78	76	80
5	85	77	80	78	82
6	89	80	85	84	89
7	91	85	89	87	95
8	100	90	93	92	98
9	100	92	98	96	100
10	100	100	100	100	100
Average	85.5	85.0	82.3	81.4	85.4

In Figure 5. Describe overall average accuracy for all four subjects. Subject 1 shows 86 % average accuracy for selection of both the level of appliance target menu. Subject 2 provides 83% average accuracy. Subject 3 and Subject 4 average accuracy is 82.1 and 80.5 respectively. Subject 1 performing well in all subjects.

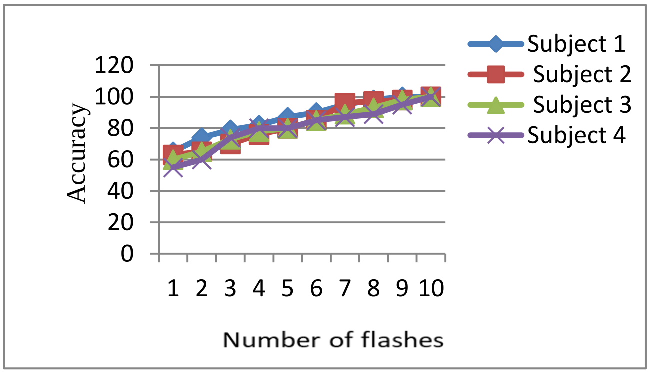

Figure 6. Accuracy prediction verses number of flashes graph of all subject.

A. Statistical analysis:

The Friedman test was employed for statically comparison between different algorithms. It is a non-parametric test preferred over repeated-measure ANOVA. We can say that this test is equivalent to repeated measure ANOVA. This test concept is that different classification methods are ranked according to their performance. The best performing method get ranked 1 the second one get rank 2 and so on. The Friedman test is employed based on the average ranks obtained by different approaches. A null hypothesis is tested for finding the p-value. A p-value is compared to the confidence level. The condition is that if p-value is less than confidence level then there is no difference between individuals, the approach will reject. In this case, post hoc Nemenyi test is employed. Next condition is that if p-value is greater than confidence level, then there is rank difference between a pair is larger than the critical difference (CD) at a certain confidence level, in this condition performance will be significantly different. The Friedman test was applied for three different classification approaches (SVM- rbf, ANN 1 layer, ANN 2 layer, SVM-linear) across all four different subjects (obtained using 10 trails). As per experimental result, the computed P-value was 0.01874 less than the confidence level. As per rule null hypothesis was rejected and Post Hoc test was employed. The obtained CD value is 3.2135 greater than p-value 0.05. The result of the post hoc test for all three is shown in Figure 7. In the coloured line average ranked of each method shown as an ascending order. Coloured line also shown that there is no significant difference between the approaches. From Figure. 7 it is observed that ANN 2 layer classifier average rank was one. This means this classification method best performing method for all subject. It can be also observed that ANN 2 layer method is best performing method than SVM-rbf and SVM-linear. Hence based on statistical analysis we can say that ANN 2 layer classification method perform better than existing method.

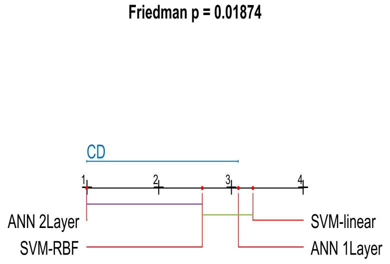

Figure 7. Schematic diagram of Nemenyi post hoc test for comparison of different classification approaches.

VI. DISCUSSION AND FUTURE SCOPE

The aim of our research work used to be providing P300 speller for home appliances control system for purely disable people that solve the problem of user convenient, and poor accuracy. Regarding this, SVM and artificial neural network (ANN) classifier methods has been proposed. Firstly using the suggested classification schemes and captured data from neurosky mind wave mobile headset for purely disable people, we are able to predict the target appliance in 10 trails. The purpose of correct target appliance fulfil in just 10 trails (provided 15 trails for classification) which ensure lesser execution time for recording the dataset. Secondly, the result shows the proposed classification achieved high classification accuracy with the new testing sample as well. Thirdly our work was design a paradigm for purely paralysed people those result ensure that this paradigm is user convenient for purely paralysed person. In near future we will work on control appliance in real Enviourment and include paralysed patients to our study and increase reliability of the system.

VII. CONCLUSION

The aim of this article provides a user convenient system, high accurate, less execution time, convenient design paradigm for purely paralysed people. For fulfil those purpose we proposed P300-based system design. By proper selection of features SVM and ANN classifier provides high accuracy with better transfer rate. ANN classifier gives better result than SVM. ANN Classifier gives 85% average accuracy in respect to levels and average target character prediction 86 % within 10 trails. Average classification accuracy of subject 1 is approximate 86%. Subject 1 performing well as compared to all four subjects.

REFERENCES

1. L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and clinical Neurophysiology*, vol. 70, pp. 510-523, 1988.
2. R. Fazel-Rezai, *et al.*, "P300 brain computer interface: current challenges and emerging trends," *Frontiers in neuroengineering*, vol. 5, p. 14, 2012.
3. J. D. Bayliss, "Use of the evoked potential P3 component for control in a virtual apartment," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 11, pp. 113-116, 2003.
4. U. Hoffmann, *et al.*, "An efficient P300-based brain–computer interface for disabled subjects," *Journal of Neuroscience methods*, vol. 167, pp. 115-125, 2008.
5. C. Guan, *et al.*, "High performance P300 speller for brain-computer interface," in *IEEE International Workshop on Biomedical Circuits and Systems, 2004.*, 2004, pp. S3/5/INV-S3/13.
6. G. Townsend, *et al.*, "A novel P300-based brain–computer interface stimulus presentation paradigm: moving beyond rows and columns," *Clinical neurophysiology*, vol. 121, pp. 1109-1120, 2010.
7. L. Acqualagna and B. Blankertz, "Gaze-independent BCI-spelling using rapid serial visual presentation (RSVP)," *Clinical neurophysiology*, vol. 124, pp. 901-908, 2013.
8. B. Blankertz, *et al.*, "A note on brain actuated spelling with the Berlin brain-computer interface," in *International Conference on Universal Access in Human-Computer Interaction*, 2007, pp. 759-768.
9. M. S. Treder, *et al.*, "Gaze-independent brain–computer interfaces based on covert attention and feature attention," *Journal of neural engineering*, vol. 8, p. 066003, 2011
10. R. Corralejo, *et al.*, "A P300-based brain–computer interface aimed at operating electronic devices at home for severely disabled people," *Medical & biological engineering & computing*, vol. 52, pp. 861-872, 2014.
11. F. Aloise, *et al.*, "Asynchronous P300-based brain-computer interface to control a virtual environment: initial tests on end users," *Clinical EEG and neuroscience*, vol. 42, pp. 219-224, 2011.
12. E. A. Aydin, *et al.*, "Region based Brain Computer Interface for a home control application," in *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*, 2015, pp. 1075-1078.
13. N. Wahy and W. Mansor, "EEG based home lighting system," in *2010 International Conference on Computer Applications and Industrial Electronics*, 2010, pp. 379-381.
14. W. Alrajhi, *et al.*, "Smart home: toward daily use of BCI-based systems," in *Informatics, Health & Technology (ICIHT), International Conference on*, 2017, pp. 1-5.
15. M. Wang, *et al.*, "A Fan Control System Base on Steady-State Visual Evoked Potential," in *Computer, Consumer and Control (IS3C), 2016 International Symposium on*, 2016, pp. 81-84.
16. K. C. Tseng, *et al.*, "Brain computer interface-based multimedia controller," in *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2012 Eighth International Conference on*, 2012, pp. 277-280.
17. A. M. Chowdhury, *et al.*, "Brain controlled assistive buzzer system for physically impaired people," in *Electrical, Computer and Communication Engineering (ECCE), International Conference on*, 2017, pp. 666-669.
18. C.-T. Lin, *et al.*, "Brain computer interface-based smart living environmental auto-adjustment control system in UPnP home networking," *IEEE Systems Journal*, vol. 8, pp. 363-370, 2014.

AUTHORS PROFILE

Praveen Kumar Shukla received the degree in electronics and communication engineering and the M.Tech. degree in control and automation from VIT Vellore, and currently pursuing Ph.D. in engineering from National Institute of Technology, Raipur. His research area includes Machine Learning, Brain-Computer Interfacing, and Biomedical Signal Processing. He has authored several research articles in aforementioned areas.

Rahul Kumar Chaurasiya received the B.Tech. degree from the Maulana Azad National Institute of Technology, Bhopal, India, in 2009, and the M.E. degree in System Science and Automation from the Indian Institute of Science, Bangalore, in 2011. He received his Ph.D. degree in 2017 from National Institute of Technology, Raipur. He was a Senior Software Engineer with Brocade Communications Systems, Bangalore, in 2011-12. During 2013-18, he was Assistant Professor at the National Institute of Technology, Raipur. Since 2019, he is with the Malviya National Institute of Technology Jaipur as Assistant Professor.

His research area includes Machine Learning, Pattern Recognition, Brain-Computer Interfacing, Optimization, Biomedical Signal Processing. He has authored several research articles in aforementioned areas. He has supervised 7 M Tech and 50 B Tech students in his area of research. He is currently supervising 5 PhD (As supervisor and Joint Supervisor) and 7 B Tech students.

Shrish Verma received the degree in electronics and telecommunication engineering and the M.Tech. degree in computer engineering from IIT Kharagpur, and the Ph.D. degree in engineering from Pt. Ravi Shankar Shukla University Raipur. He is currently the Dean academic and a Professor with the Department of Electronics and Telecommunication Engineering, National Institute of Technology, Raipur. He has authored over 50 research papers in various journals and conferences in the field of computer and communication networks, distributed processing, data mining and analysis, text analytics and software engineering.