International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Novel Approach for EEG Signal Processing Based on Gradient Bilateral Support Vector Machine for Bioengineering Applications

[1]Amit Kumar Bishnoi, [2]Sachin Jain, [3]Sanjay Nautiyal, [4]Rengarajan A.

Submitted: 19/08/2023 **Revised**: 08/10//2023 **Accepted**: 21/10/2023

Abstract*:* Electroencephalography (EEG) is one of the most effective methods in the area of bioengineering for comprehending how the brain works in humans. Analysing and understanding the electrical signals collected from the head depends heavily on EEG processing of signals. This non-invasive method offers insightful information on how the brain functions and has numerous uses in clinical diagnostics, neurology, and brain-computer interfaces. The electric possibilities produced by the brain's millions of cells working in unison are what the EEG analyses. An array of electrodes carefully positioned on the scalp can be used to record these electrical signals, often known as brain waves. The resulting EEG signal is a complicated time series that contains extensive data about the functioning of the brain, including details about cognitive processes, emotions, and other neurological conditions. High temporal accuracy of the raw EEG signal enables researchers and physicians to observe quick changes in brain activity. However, a number of noise sources, such as skeletal artefacts, eye motions, and influence from surroundings, also taint it. The EEG data must therefore be processed effectively in order to retrieve pertinent data. EEG signal processing has helped develop numerous fields in bioengineering applications. It has illuminated the systems underpinning perception, attention, memory, and sleep in neuroscience studies. EEG analysis helps in the diagnosis and follow-up of epilepsy, sleep problems, brain traumas, and neurodegenerative illnesses in medical settings. By allowing people with movement limitations to control external gadgets with their brain activity, brain-computer interfaces based on EEG have expanded the field of neurorehabilitation and assisted technology.

Keywords: *Electroencephalogram (EEG), neural network, deep learning method, machine learning, bioengineering*

1. Introduction

Electroencephalography (EEG) is one of the most effective methods in the field of bioengineering for comprehending how the human brain functions. Analysing and understanding the electrical activity recorded from the scalp depends heavily on EEG signal processing. This non-invasive method offers insightful information on how the brain functions and has numerous uses in clinical diagnostics, neurology, and neuroscience [1]. The electric potential produced by the brain's millions of cells working in unison are what the EEG analyses. A series of sensors carefully positioned on the scalp can be used to record these electrical impulses, often known as brainwaves. The ensuing EEG signal is a complicated time series that contains extensive data about the functioning of the brain, including data pertaining to cognitive processes, emotions, and other neurological conditions [2].

[1]*Assistant Professor, College of Computing Science and Information Technology, Teerthanker Mahaveer University, Moradabad, Uttar Pradesh, India, Email id: amit.vishnoi08@gmail.com*
[2]*Assistant professor, School of Computer Science & System, JAIPUR NAITONAL UNIVERSITY, JAIPUR, India, Email Id: sachin.jain@jnujaipur.ac.in*
[3]*Assistant Professor, School of Management & Commerce, Dev Bhoomi Uttarakhand University, Uttarakhand, India, Email Id: somc.sanjay@dbuu.ac.in*
[4]*Professor, Department of Computer Science and IT, Jain(Deemed-to-be University), Bangalore-27, India, Email Id: a.rengarajan@jainuniversity.ac.in*

High temporal accuracy of the raw EEG signal enables researchers and physicians to track rapid shifts in neural activity. However, a number of noise sources, such as skeletal artefacts, eye movements, and interference from the environment, also taint it. Consequently, efficient signal processing methods are required for getting relevant information from the EEG data. The analysis of EEG signals has helped develop numerous fields in bioengineering applications. It has illuminated the systems underpinning perception, attention, memory, and sleep in neurological studies. EEG analysis helps in the diagnosis and follow-up of epilepsy, sleep disorders, brain traumas, and neurodegenerative illnesses in medical settings [3]. By allowing people with movement limitations to control external gadgets with their brain activity, interfaces for brain computers based on EEG have expanded the field of neurorehabilitation and assistive technology. Machine learning methods have become efficient instruments for automated EEG signal interpretation. Researchers and doctors may increase diagnosis accuracy, create cutting-edge apps, and extract useful details from EEG data by utilising the abilities of machine learning techniques [4]. The development of algorithms that can autonomously categorise, analyse, and retrieve pertinent information from EEG signals is the main goal of EEG signal processing utilising machine learning. Algorithms based on machine learning can be trained to spot connections and patterns in the data, allowing the creation of accurate models for a variety of uses. Machine learning-based EEG signal processing has a wide range of applications. It can help with the diagnosis of neurological conditions like epilepsy, sleep issues, or injuries to the brain. Additionally, machine learning models can be applied to analyse mental states, spot emotional or psychological task patterns, and even enable brain-controlled interface for assistance or therapy technology [5].

Thus, Gradient Bilateral Support Vector Machine (GBSVM) is a cutting-edge technique used in this research to apply EEG signal processing. We initially collected the EEG raw dataset to analyze the efficiency of the suggested GBSVM approach.The rest of this paper is as follows: part 2 is a literature review; Part 3 contains the proposed method explained; Part 4 includes the results and analysis; and Part 5 Discusses the conclusion.

2. Related works

Study [6] applied and contrasted deep learning techniques for convolutional neural networks (CNN) and deep neural networks (DNN) for the assessment of cybersickness from EEG data. In addition, they offer information preparation for learning and signal integrity weights that will enable us to learn EEG data using deep learning algorithms at high speeds. Study [7] used noninvasive machine learning algorithms to identify speech laterality from EEG signals. Various Convolutional Neural Networks (CNN) designs, including VGG16, VGG19, ResNet, MobileNet, NasNet, and DenseNet, were used to construct spectrograms for each of the 18 EEG channels. The spectrograms' characteristics were extracted using these types of structures. Though not realistically practicable, the study's categorization results are encouraging and pave the path for further research. The proposed study [8] uses the DEAP benchmark database to construct a mood recognition technique that is subject-independent. In the survey, low-high polarity and equally low-high excitation are classified using deep neural networks with simple architecture. Machine learning techniques are currently recognized for categorizing biological signals and for high success rates for the automated diagnosis of a wide range of disorders. In a study [9], the categorization of alcohol-related electroencephalographic (EEG) data is demonstrated using Wavelet Packet Decomposition (WPD) and MLT. They have had success using our approach to categorize EEG data from intoxicated individuals. There are computer-aided diagnostic techniques (CAT) using the discrete wavelet transform (DWT) and math compression presented in the study [10] to regulate signals and epileptic episodes. The proposed method successfully identified epileptic seizure activity in EEG data using a combination of non-linear and linear machine-learning classifiers. As a result, using simplified linear models, their CAD method can reliably discriminate between EEG activity associated with epileptic seizures and seizure-free and normal EEG activities.

The research is based on electroencephalogram (EEG) data analysis and machine learning methods via accounting. study [11] provided a feasible way for recognizing sleep stages. A band-pass filter is used to filter and divide EEG signals into frequency sub-bands. With varying sampling dimensions, aspects of statistics are retrieved and learned using decisions tree, SVM, and Random Forest approaches. Study [12] examine Machine Learning (ML) and Deep Learning (DL) algorithms for using EEG brainwave data to categorize traumatic events. It predicts either positive, neutral, or unfavorable human emotions from EEG signals using various techniques and procedures. The contribution happens throughout the data processing stage, particularly at the classification stage. They discover that InfoGain regularly enhances RF's analysis capabilities and performs better than competing classifiers. A study [13] compared two stages of visual processing in identifying unique EEG signals linked to each step and then used a classifier to separate the two processes. Attributes collected from two time and frequency domains were used to identify both stages defined by these study-test intervals. Individual machine learning classifiers were trained using these a convolutional neural network (CNN) was prepared using the signal's representations in the time-frequency domain. The forecasting method was recommended by the study [14] to determine consumer preferences for the online (E-commerce) procedure. Individuals of various ages were shown multiple products, and their EEG signals and preferences were collected. Artificial neural networks and other classification algorithms, including Logistic Regression, Decision Tree Classifier, K-Nearest Neighbours, and Support Vector Machine, achieved product- and subject-level categorization using a user-independent testing technique. A study [15] examined whether machine learning methods can be used to diagnose schizophrenia by developing machine learning classifiers of schizophrenia utilizing passive EEG data. Finally, five well-known machine learning algorithms employed these elements as characteristics: support vector machines (SVM), decision trees (DT), random forest (RF), and k-nearest neighbors (KNN). According to their research, the suggested analytic process for resting state EEG data may quickly determine and choose a collection of characteristics that conventional machine learning algorithms may successfully employ to distinguish schizophrenia patients from healthy individuals.

3. Proposed Method

Gradient Bilateral Support Vector Machine (GBSVM), a technique for classification that is extensively used for EEG signal processing, is presented in this study. We first gather the EEG raw information to evaluate how effective the suggested GBSVM method is. A wiener filter is then applied during the pre-processing stage to decrease the distortion in the raw data. Independent component analysis (ICA) is used to pinpoint important aspects to enhance EEG processing properly. Figure 1 depicts the overview of the methodology.

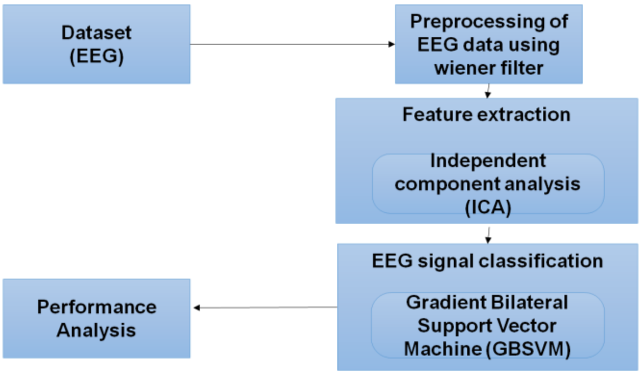

Fig 1: Overview of Methodology

3.1 Dataset

The public UCI epileptic seizure recognition data set collects information used in this study. There are five separate folders with 120 files in the original data collection. To be more precise, each file reflects a recorded sample of one of the subject's neural activities. Each file contains a monitoring of brain activity for 20.4 s and 6024 data points. This means that the data set has 600 participants, each with a recording sample with 6024 points of information.

3.2 Prepossessing

The wiener filter is a widely used image processing technique for eliminating extraneous information from the Multimodal Medical image. Our approach converted the input image into a two-dimensional representation with pixels having values between 0 and 255. The Multimodal Medical image was further altered using the same method to execute matrix operations. Since the Wiener filter uses a linear estimation of the original image, it removed additive noise and lowered mean square error. Equation 1 and Equation 2 thereby calculated the mean and variance of each pixel.

$$\mu_{a,b} = \frac{1}{AB} \sum_{x,y \in N} P(x,y) \qquad (1)$$

$$\sigma^2{}_{a,b} = \frac{1}{AB} \sum_{x,y \in N} P(x,y)^2 - \mu^2$$
(2)

Here, P is an input image, x and y are filtering pixels, N=X=3 are surrounding pixels, and x and y are placed in an NxX block.

$$P_{(a,b)} = \mu + \frac{\sigma^2 - n^2}{\sigma^2} \left(P(x-y) - \mu \right)$$
(3)

In Equation 3, where $n2$ is the noise variance, changes according to the Wiener filter are made.

3.3 Feature extraction

3.3.1 Independent Component Analysis

The ICA is an advanced order statistical unsupervised learning algorithm. The best way to determine the linear transformation would be from the information itself, as this would allow the conversion to be perfectly tailored to the type of data getting handled. The underlying vector for conventional transformations becomes fixed transforms, which means they remain unchanged regardless of any information. We can utilize the statistical hidden variable model to define ICA. We observe n random variables $x_1, \ldots .\, x_n$, which are modeled as a linear combination of n random variables $s_1 \ldots \ldots .\, s_n$:

$$x_1^S w + a_1 = 0 \; and \; x_2^S w + a_2 = 0$$
(4)

where the real variables $i, j = 1, \ldots, n$ and s_i are present. The s_i is empirically independent of each other by convention. This is the fundamental ICA model. Since the independent components si are latent variables, it is impossible to track them immediately. Additionally, it is believed that the combination coefficient is uncertain. We only see the random variable x_i hence we must use x_i to figure out the independent components and the mixing coefficient a_{ij} Under a general set of assumptions, this is possible. The combination concept is expressed as follows in vector-matrix notation:

$$x = As = \sum_{i=1}^{n} a_i s_i$$
(5)

In text processing, this model is seen as a linear set of basic variables. Additionally, the basis vectors are localized in frequency, direction, and space. We aim to locate a suitable set of basis vectors to adequately depict iris patterns.

3.4 Classification

3.4.1 BSVM

A bilateral Support Vector Machine seeks two non-parallel hyperplanes given by $x_1^S w + a_1 = 0 \; and \; x_2^S w + a_2 = 0$ obtained by solving the following optimization problem:

$$Min\, x_1, a_1, \xi_2 \; \frac{1}{2} \sum_{j=1}^{k_1} e\left(w_j^+\right) + d_1 \sum_{i=1}^{k_2} K\left(w_i^-, z, e(w_i)\right), \qquad (6)$$

And

$$Min\, x_2, a_2, \xi_1 \; \frac{1}{2} \sum_{j=1}^{k_2} e\left(w_j^-\right) + d_2 \sum_{i=1}^{k_1} K\left(w_i^+, z, e(w_i)\right), \qquad (7)$$

Where $c_1 \geq 0$ ($c_2 \geq 0$) are, respectively, points from classes +1 and -1. Additionally, L (.) designates the erroneous value where the points of class -1 (+1) are closer to the class +1 (-1) hyperplane than the unit length. This ultimately results in the following two quadratic programming issues:

(GBSVM 1) $Min\ x_1, a_1, \xi_2\ \frac{1}{2}||Bx_1 + f_1 a_1||^2 + d_1 f_2^S \xi_2$

$subject\ to - (Ax_1 + f_2 a_1) + \xi_2 \geq f_2, \quad \xi_2 \geq 0$

(8)

And

(GBSVM 2) $Min\ x_2, a_2, \xi_1\ \frac{1}{2}||Bx_2 + f_2 a_2||^2 + d_2 f_2^S \xi_2$

$subject\ to (Bx_2 + f_2 a_2) + \xi_1 \geq f_1, \quad \xi_1 \geq 0$

(9)

Where $f_1, f_2 \geq 0$ are vectors of ones with the required dimensions, and $(x_{t,}^+ + 1) and (x_{t,}^- - 1)$ is the trade-off value between the proximity of the hyperplane to its class and the sum of erroneous vectors attributable to samples of class 1 (class +1). The proximity of a new test point X to the sample hyperplanes of the two classes determines the class label Y of that point.

3.4.2 Gradient Bilateral Support Vector Machine

The Quadratic Programming Problems equations identical and were transformed by GBSVM into the subsequent unconstrained minimizing issues.

$$min\ x_1, a_1\ \frac{1}{2}\left(||x_2||^2 + a_1^2\right) + \frac{d_1}{2k_1}||Bx_1 + f_1 a_1||^2 + \frac{d_2}{k_2} f_2^S (f_2 + Ax_1 + f_2 a_1) +,$$

(10)

And

$$\boldsymbol{min\ x_2, a_2\ \frac{1}{2}\left(||x_2||^2 + a_2^2\right) + \frac{d_1}{2k_2}||Bx_2 + f_2 a_2||^2 + \frac{d_2}{k_1} f_1^S}$$

(11)

Where $\boldsymbol{d_1, d_2 \geq 0}$ is the proper hinge-loss operation, which swaps a vector's negatives element with zero, and trade-off factors. To generate an array of instantaneous variables while iteratively resolving problems and GBSVM uses samples from two classes,$(\boldsymbol{X_{t,}^+ + 1})$ and $(\boldsymbol{x_{t,}^- - 1})$and sub-gradients concerning $\boldsymbol{f_1, b_1, and\ b_2}$

$$\nabla x_{1,s} e_{1,s} = x_{1,S} + d_1\left(x_1^S, w_s^+ + a_{1,s}\right) w_s^+\ d_2 w_s^- sign\left(1 + x_1^S, w_s^- + a_{1,s}\right) +, \quad (12)$$

And

$$\nabla x_{2,s} e_{2,s} = x_{2,S} + d_1\left(x_2^S, w_s^+ + a_{2,s}\right) w_s^+\ d_2 w_s^- sign\left(1 + x_2^S, w_s^- + a_{2,s}\right) +,$$

(13)

$$\nabla a_{2,s} e_{2,s} = a_{2,S} + d_1\left(x_2^S, w_s^+ + a_{2,s}\right) w_s^+ + w_s^- sign\left(1 + x_2^S, w_s^- + a_{2,s}\right) +,$$

(14)

Respectively GBSVM iteratively updates $\omega_{1,t}, \omega_{2,t,b_1,}$ and $b_{2,t}$ with some predefined step-size α. If certain predetermined termination requirements are met, the process is terminated. Similar to GBSVM, a new test point's label $\chi \epsilon R^n$ is assigned.

It is demonstrated that the GBSVM algorithm will eventually find an optimum solution. Still, it is unknown whether there is an upper bound on the number of iterations that can be utilized. Additionally, as was previously noted, just one pair of points in repetition t could differ from its path of lineage. As a result, the algorithm may need additional iterations to converge. Additionally, GBSVM is susceptible to poor adaptation, which harms the method's integration, comparable to a restriction in most stochastic gradient estimation methods.

4. Result

In this section we evaluate the performance of the proposed method with exisiting methods. The parameter such as accuracy, precision, recall and f1-score. The exisiting method such as CNN, LSTM.

Accuracy is a metric for how well a model forecasts the results or labels of a specific dataset. It is computed by dividing the total number of forecasts made by the number of accurate predictions, commonly expressed as a percentage. Figure 1 depicts the accuracy outcome. The value obtained for our suggested approach is superior to current methods (CNN, LSTM). This demonstrates that our recommended strategy (GBSVM) which is effective.

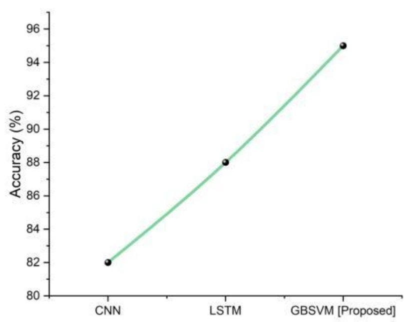

Fig 1: Result of Accuracy result

A statistical parameter called precision assesses the categorization or prediction model's accuracy out of all occurrences anticipated to be favorable. It calculates the percentage of correctly predicted positive instances (true positives). The value obtained using our suggested approach (GBSVM) is superior to the current methods(CNN, LSTM). This demonstrates that our proposed strategy which is effective

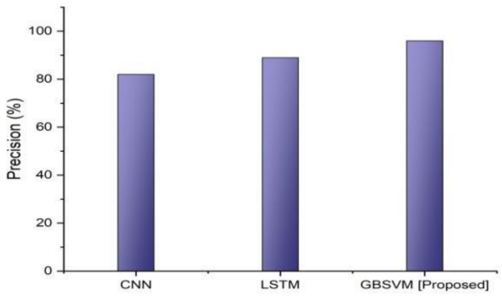

Fig 2: Result of precision

Recall, also called sensitivity or true positive rate, quantifies the percentage of positive occurrences the model properly accepted. The true positive to total correct and misleading negative ratio is calculated. Compared to the existing approaches (CNN, LSTM), the value produced using our proposed method (GBSVM) is higher. This shows that our proposed way is effective

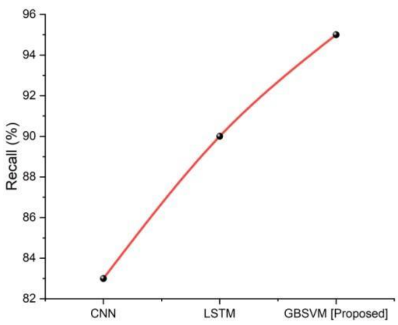

Fig 3: Result of recall

The F1-score is sometimes referred to as the F-score or F-measure. Precision's harmonic mean is referred to as the F1-score. When compared to the existing approaches (CNN, LSTM), our proposed method (GBSVM) is better. This shows that our proposed way is effective in locating an effective

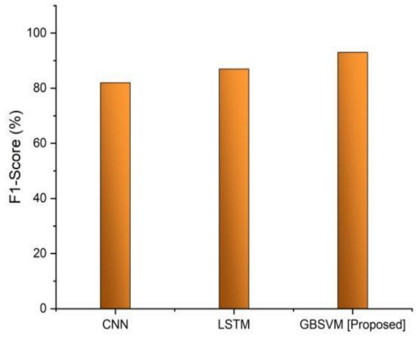

Fig 4: Result of f1-score

5. Conclusion

In bioengineering research, applying a Gradient Bilateral Support Vector Machine (GBSVM) for EEG signal processing yields encouraging results. EEG signals are difficult to analyze and comprehend due to their level of detail and variation [16]. However, these issues are addressed by the proposed GBSVM method. A basic dataset of EEG signals is first gathered for the study's processing. A wiener filter is used in the preprocessing stage to lower distortion in the raw data and boost the clarity of the signal. The next step is to use Independent Component Analysis to pinpoint important EEG data characteristics, improving the process's validity. Using the retrieved capabilities, the suggested processing method efficiently handles the EEG data. Despite having a low degree of spatial accuracy, EEG data can provide insights into the electrical signals of the brain. Innovations in collecting features, deep learning, multisensory integrating, immediate use, personalised treatment, and moral issues could be made in the future of processing EEG signals utilising machine learning techniques.

References

[1] Abdulrahman, A., Baykara, M. and Alakus, T.B., 2022. A Novel Approach for Emotion Recognition Based on EEG Signal Using Deep Learning. Applied Sciences, 12(19), p.10028.

[2] Chen, X., Li, C., Liu, A., McKeown, M.J., Qian, R. and Wang, Z.J., 2022. Toward open-world electroencephalogram decoding via deep learning: A comprehensive survey. IEEE Signal Processing Magazine, 39(2), pp.117-134.

[3] Ieracitano, C., Mammone, N., Bramanti, A., Marino, S., Hussain, A. and Morabito, F.C., 2019, July. A time-frequency-based machine learning system for brain states classification via eeg signal processing. In 2019 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.

[4] Hu, L. and Zhang, Z. eds., 2019. EEG signal processing and feature extraction (pp. 1-437). Singapore: Springer Singapore.

[5] Li, G., Lee, C.H., Jung, J.J., Youn, Y.C. and Camacho, D., 2020. Deep learning for EEG data analytics: A survey. Concurrency and Computation: Practice and Experience, 32(18), p.e5199.

[6] Jeong, D., Yoo, S. and Yun, J., 2019, March. Cybersickness analysis with EEG using deep learning algorithms. In 2019 IEEE conference on virtual reality and 3D user interfaces (VR) (pp. 827-835). IEEE.

[7] Toraman, S., Tuncer, S.A. and Balgetir, F., 2019. Is it possible to detect cerebral dominance via EEG signals using deep learning? Medical hypotheses, 131, p.109315.

[8] Pandey, P. and Seeja, K.R., 2019. Subject-independent emotion detection from EEG signals using deep neural network. In International Conference on Innovative Computing and Communications: Proceedings of ICICC 2018, Volume 2 (pp. 41-46). Springer Singapore.

[9] Rodrigues, J.D.C., RebouçasFilho, P.P., Peixoto Jr, E., Kumar, A. and de Albuquerque, V.H.C., 2019. Classification of EEG signals to detect alcoholism using machine learning techniques. Pattern Recognition Letters, 125, pp.140-149.

[10] Amin, H.U., Yusoff, M.Z. and Ahmad, R.F., 2020. A novel approach based on wavelet analysis and arithmetic coding for automated detection and diagnosis of epileptic seizure in EEG signals using machine learning techniques—Biomedical Signal Processing and Control, 56, p.101707.

[11] Santaji, S. and Desai, V., 2020. Analysis of EEG signal to classify sleep stages using machine learning. Sleep and Vigilance, 4, pp.145-152.

[12] Klibi, S., Mestiri, M. and Farah, I.R., 2021, July. Dynamic behavior analysis based on EEG signal processing using Machine Learning: A case study. In 2021 International Congress of Advanced Technology and Engineering (ICOTEN) (pp. 1-7). IEEE.

[13] Mathur, N., Gupta, A., Jaiswal, S. and Verma, R., 2021. Deep learning helps EEG signals predict different stages of visual processing in the human brain—Biomedical Signal Processing and Control, 70, p.102996.

[14] Ullah, A., Baloch, G., Ahmed, A., Buriro, A.B., Junaid, A., Ahmed, B. and Akhtar, S., 2022. Neuromarketing solutions based on EEG signal analysis using machine learning. International Journal of Advanced Computer Science and Applications, 13(1).

[15] deMiras, J.R., Ibáñez-Molina, A.J., Soriano, M.F. and Iglesias-Parro, S., 2023. Schizophrenia classification using machine learning on resting-state EEG signal. Biomedical Signal Processing and Control, 79, p.104233.

[16] Dr. Gupta, S. K. & Artono, B. (2022). Bioengineering in the Development of Artificial Hips, Knees, and other joints. Ultrasound, MRI, and other Medical Imaging Techniques. Technoarete Transactions on Industrial Robotics and Automation Systems (TTIRAS). 2(2), 10–15.

[17] Shende, P. ., Vishal Ashok, W. ., Limkar, S. ., D. Kokate, M. ., Lavate, S. ., & Khedkar, G. . (2023). Assessment of Seismic Hazards in Underground Mine Operations using Machine Learning. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 237–243. https://doi.org/10.17762/ijritcc.v11i2s.6142

[18] White, M., Hall, K., López, A., Muñoz, S., & Flores, A. Predictive Maintenance in Manufacturing: A Machine Learning Perspective. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/154

[19] Dhabliya, D. Security analysis of password schemes using virtual environment (2019) International Journal of Advanced Science and Technology, 28 (20), pp. 1334-1339.