https://doi.org/10.51153/kjcis.v5i1.107

EEG-Based BCI for Attention Assessment in E-Learning Environment using SVM

Muhammad Bilal[1] Muhammad Marouf [2] Safdar Rizvi[3]

Fatima Bashir[4] Muhammad Shahzad[5] Jawad Ahmed Bhutta[6]

Abstract

In this era, technology has paved the way to new dimensions of research in academia in terms of students' performance, learning outcomes, and capability. Brain-Computer Interface (BCI) has shown to be essential in monitoring students' brain activity through electroencephalogram (EEG) signals. Attention is a prerequisite to the evaluation of the student learning process. This paper proposed recognition of attention level in an e-learning environment. It was divided into two states, attention, and inattention(distracted). EEG signals were extracted using the non-invasive device (Emotiv Insight) and processed data for noise removal through the Finite Impulse Response (FIR) filter. A machine learning approach has been used for the classification of data. The data acquired through the channels is continuous for which Support vector machines (SVM) have been used for classification. The selected features are then classified. The obtained accuracy for attention level is 90.07% in an e-learning environment.

Keyword: Brain-Computer Interface, Electroencephalogram, Attention, Machine Learning

1. Introduction

Brain-Computer Interface (BCI), the understanding intended to explain the purpose through which the signals are produced. An extensive study has been done to design valuable and efficient systems that provide an effective and interactive service using human biological signals [1],[2]. The individual's neural system can help to yield these signals. Whereas the human heart can obtain the Electrocardiograph (ECG) signals [3], an individual's hand muscle can attain Electromyogram (EMG) signals and the scalp of the human brain can achieve Electroencephalogram (EEG) signals [4]. The EEG is used by BCI systems for monitoring and analyzing the signals of the human brain [3],[5].

[1]*Department of Computer Science, Bahria University, Karachi | bilalvohra.bukc@bahria.edu.pk*
[2]*Department of Computer Science, Bahria University, Karachi | mmarouf.bukc@bahria.edu.pk*
[3]*Department of Computer Science, Bahria University, Karachi | safdar.bukc@bahria.edu.pk*
[4]*Department of Computer Science, Bahria University, Karachi | fatimabashir.bukc@bahria.edu.pk*
[5]*Department of Computer Science, Bahria University, Karachi | muhammadshahzad.bukc@bahria.edu.pk*
[6]*Department of Computer Science, Bahria University, Karachi | jawadbhutta.bukc@bahria.edu.pk*

For several years, the brain-computer interface (BCI) has been a theme of research that connects the human brain and computer [6]. From previous decades, Researchers have made an outstanding pathway in practical BCI applications and made sure that these interfaces are part of several technological visions [8]. BCI is mainly contributing to attention analysis, which is a basic part of human productivity.

Attention is an important aspect of the educational environment [9] and may affect learning processes positively or negatively according to its level. In the twenty-first century, the increase of digital media has led to very rapid advancement in the use of videos in an educational medium [10]. Video-based education has become a progressively popular technique in e-learning. E-learning means learning activities through internet tools outside the traditional classroom. Due to its usefulness, learners can learn from online video via mobile devices, tabs, or computers beyond the time-space limitation [11]. Several various video-based learning platforms, such as TED, Coursera, YouTube, and MOOCs, started to facilitate different video courses for learners. The platforms which are based on education purposes usually allow teachers to upload well-prepared videos based on their teaching plans. This mode of learning formed a new learning method, which is different from the customary classroom-based or text-based learning. Thus the purpose of the research is to use EEG technology to study that in what way video-based lectures in an e-learning environment setting affect the attention level and its impact on the learner, and further apply feature extraction and machine learning technique. The outcomes of the study show the contribution by analyzing the significance of the attention factor in an e-learning environment.

2. Background Knowledge

A. Brain-Computer Interface

The Brain-Computer Interface system is schematically shown in Figure 1. It is widely used as an integrated diagnostic tool to analyze brain signals and patterns by placing electrodes on the scalp. It gives real-time data. The mental syndromes and brain patterns are identified by the general info of functional, physical, and pathological status of the brain contained by EEG for diagnosing and recording brain activity. The first prototype of BCI came out in 1973, in the laboratory of Dr. Vidal [7].

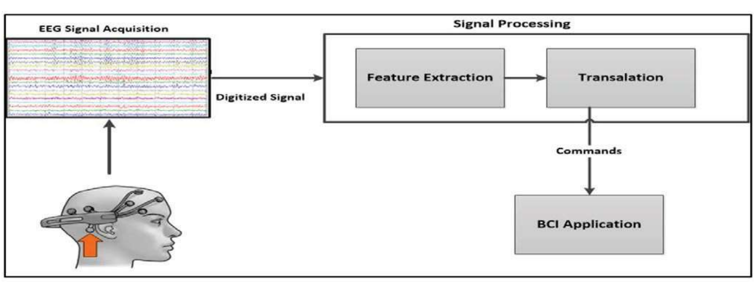

Figure 1: General brain computing interface design

In the earlier demonstration, it has reported that the EEG signals had been noticed with the fusion of different frequencies that are alpha, beta, delta, and theta signals. These types of signals are also known with multiple names like; EEG signals or brainwaves and spectral components. All these signals are visualized in Table 1 [12].

Table 1: Type of EEG spectral wave with defined ranges and their basic functions

Wave	Frequency Range	Major Functions
Delta	Up to 4 Hz	Sleep, found in attention tasks
Theta	4 Hz to 7 Hz	Halting, incompetence, related to ADHD
Alpha	8 Hz to 15 Hz	Rest, eyes closing
Beta	16 Hz to 31 Hz	Concentration, uneasy thoughts
Gamma	Above 32 Hz	Cognition

3. Literature Review

Attention imitates various activities of the human body and that is why an essential constraint of the brain. It is an activity of keeping the brain active and thoughtful as well as processing the things in the environment for particular tasks. Attention helps in gaining information for the things of better interest as well as the prediction of attention level is also a major research area nowadays [13], [14].

The attentiveness of students while learning significantly affects their learning results. The teacher's difficultly in observing the student's attentiveness to online learning can also cause a problem in determining students' attention level. The experiment on the students with EEG-related data in a controlled e-learning environment can be feasible in determining the attentiveness or inattentiveness of a student [15]. Unlike a psychologist, many BCI applications are there to analyze the attention level, which has been reported in many studies under controlled and uncontrolled environments [16], [17].

There are extensive applications and researches on determining the attention level, like exploring the learning performance and behavior of university students in English listening courses by determining their attention level through brainwave signals [18]. Provided some active and inert indications in an electronic learning environment to determine whether their attention is affecting in different circumstances studied by [19]. The excessive use of cell phones in the class can also influence the attention level of students in the learning environment [20]. Brain-Computer Interface (BCI) has been used and researched in every aspect of human life and carried out by different researchers to accomplish the research problem. This section explains different techniques used in many studies for the evaluation of students' attention via video lectures in an e-learning environment through BCI.

In [21], a review on electroencephalography (EEG) evaluation was done to observe the effects of challenge-skill balance on flow experience and the effect of flow experience on learning performance in a computer-aided environment. The outcomes determined that the challenge-skill balance of learning materials was the basis of a flow experience of learners. The classification of attentiveness and non-attentiveness in the subjects while watching the lectures via multimedia in different situations can be done using. The EEG power spectral density (PSD) features were extracted from preprocessed EEG signals in 5 frequency bands of the delta, theta, alpha, beta, and gamma and then the attentiveness and non-attentiveness were classified using the extracted features with the change in the span of a period. SVM, kNN, Ensemble, and CNN were the classifiers to identify the attentiveness and non-attentiveness situations EEG [22].

A combination of data mining algorithms like correlation-based feature selection (CFS) and KNN for the classification system has been used by [23]. The CFS+KNN algorithm has been evaluated against multiple classification algorithms such as CFS+C4.5. They measured the performance of classification using the different 3-fold cross-validation data. They collected data from 10 individuals while learning the material in a virtual distance-learning environment. The attention has been assessed on high, neutral, low levels using a self-assessment model of self-report. The interactive Brain Tagging system (IBTS) has been used to assemble the learner's attention developed. The EEG data has been used by IBTS to transform it into evaluable attention value. They recorded the individuals' attention level every second while watching a video. The constant level of attention and the variation level of attention have been envisioned while watching a video. The distinct and cooperative attention period was the outcome of this study [24].

Age is a major factor for the inspiration of visual attentiveness and reading time. The mobile electroencephalography device can measure one's consideration and attentiveness level in the reading environment [25]. In a study of [26], a system was developed to assess brainwave data. A Massive Open Online Courses (MOOCs) system and conventional techniques have been used in applicants learning. Fourier represented the brainwaves and symmetry elements in Fast Fourier transform have used to obtain Power Spectral Density (PSD) values for the analysis of data. They determined that MOOCs system in teaching methods were efficient for increasing the attention of the applicants as compared to the conventional techniques as well as providing comfortable learning for them. As an overall assessment and a part of the study, we can see in Table 2, a summary of the existing research.

https://doi.org/10.51153/kjcis.v5i1.107

Table 2: Attention level in the e-learning environment

Environment	Ref.	Sample Size	Type	Experimental Finding
E-Learning	[21]	20	Multimedia Content	Assess Challenge-skill balance and flow experience.
	[22]	8	Video	Assess attention level while applicants were instructed to watch lecture videos through multimedia.
	[23]	10	Video	Measured attention (High, Neural, and Low) based on 20 minutes of learning task and self-assessment model.
	[24]	31	Video	Analysis of proper time-period through video learning to increase the attention level of learners in learning content.
	[25]	55	Video	Measure sustained attention while students watched the same video lecture for 16 min.
	[26]	15	Video	Measure effects of attention level in learning through MOOCs system.

4. Methodology

The proposed methodology is based on an e-learning environment. The basic framework of the presented research is shown in Figure 2. The data was collected, and the learning model was designed to classify attention levels. Finite Impulse Response (FIR) filter was used to remove the noises that affect signals. Further independent component analysis (ICA) was applied to extract attention features from the noise-free signals. In the end, features were analyzed with EEG signals and tests of the participants in e-learning environments. Further, the data is classified using Support Vector Machine (SVM).

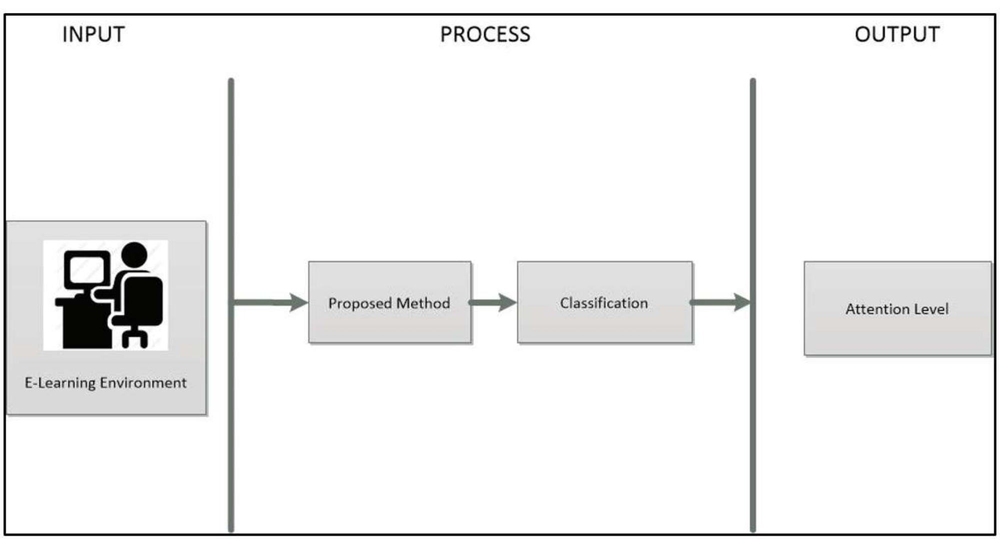

Figure 2: Basic Framework

The dataset is generated by acquiring a signal of participants. For the e-learning environment, 15 participants were selected. EEG data gathering device which has been used and the participants which were involved in the e-learning environment are described in subsections in detail.

A. Proposed Approach

Figure 3 shows the workflow of the proposed research. The first step in the proposed approach is signal acquisition. For recording signals, we used the EEG technique. EEG technique is commonly used for collecting data by the noninvasive method in which the participant wears the emotive insight headset.

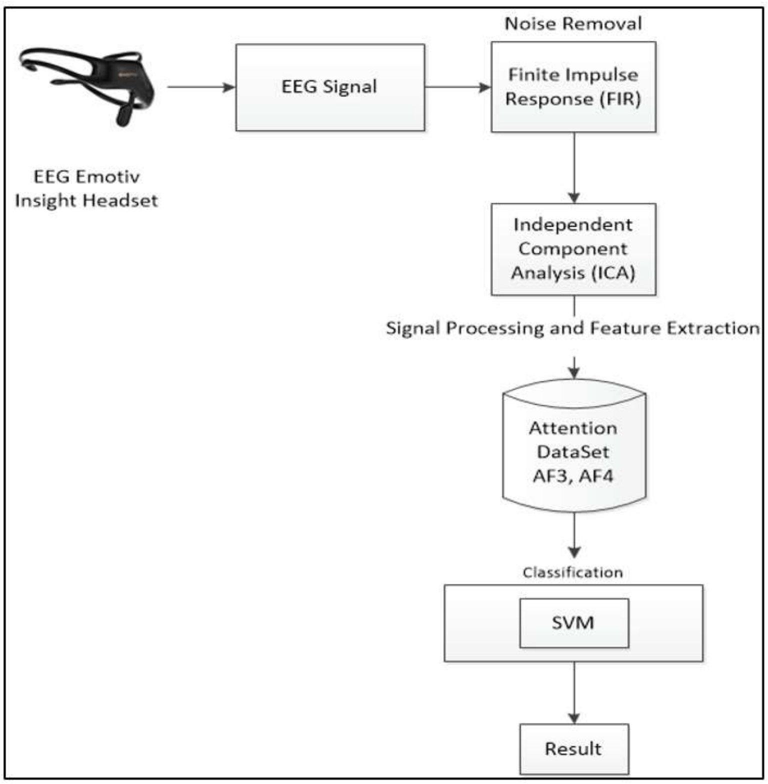

Figure 3: Workflow of the proposed methodology

B. Participants and Dataset Preparation

In this study, 15 computer science students of the 3rd year from Bahria University Karachi campus were recruited, all of whom were right-handed. Among the 15 participants, 11 were male, 4 were female, and the age was between 18 and 21 years old (Mage=18.8, SD=0.98). According to the investigation of the participants, they had no mental diseases such as epilepsy, depression, and hyperactivity disorder or did take psychoactive drugs for a long time. At present, they neither had used any drugs to change their thinking nor had any history of head injury or brain injury. The experimenter introduced the scope and procedure of the experiment to the participants and informed them that the experiment would not cause any risk to their health, to ensure that the participants could participate in the experiment voluntarily and sign the informed consent before the experiment. Because this experiment was based on learning through videos via computer devices, the participants needed to ensure that they can see the learning content. The participants are tested one by one in the laboratory environment, each was asked to sit in a comfortable chair and watch the video-based lecture using a computer and headphones for noise-free audio. During the experiment, the participants' EEG signal was simultaneously recorded as described in Figure 4.

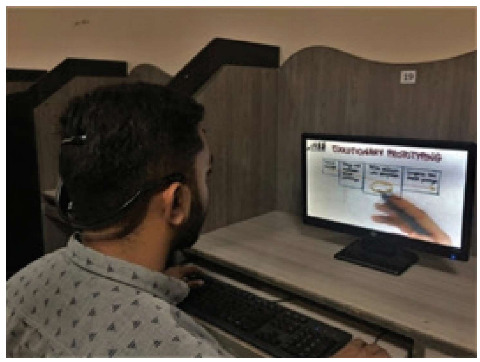

Figure 4: E-learning environment

C. Signal Acquisition

The brain signal has been accomplished by EEG noninvasive technique. This is a widely used signal acquisition technique due to its greater temporal resolution [28]. A portable EEG headset device (Emotiv Insight), introduced five main data-collection electrodes and two reference electrodes for signal acquisition. The electrodes were positioned at AF3, AF4, T7, T8, and Pz based on the international 10-20 systems. 128Hz was set as the sampling rate. During the experiments, each participant has been informed that they must be relaxed and calm. All healthy participants have been seated in a quiet room i.e. lab and the LCD monitor screen has been placed and the armchair to make the gazing level equal for the participant.

D. Artifacts Handling in E-Learning Environment

For the removal of artifacts in the E-Learning environment, EEGLAB has been used in the proposed research study. The data set is labeled with the names of the electrodes. The entire data set was labeled with the x-axis as time framework in-unit seconds and the y-axis for the frequency spectral power that is measured in micro-volts (μV). Artifact removal in the e-learning environment is performed by removing the entire unnecessary channel's data. Therefore, no further filter is needed to apply as it is a noise-free and controlled environment. In the end, this new representation of the data has been used for the preprocessing of the signals.

E. Feature Extraction

E-learning environment signals consist of numerous electrodes channels including; AF4, AF3, Pz, T7, and T8. After the ELE signal enhancement phase, each component has different spectral powers with respect to its sampling rate that are measured at 128 Hz frequencies.

Signal AF4 is the spectral power that ranges from 4100 to 4300 microvolts with time series measured at 8 seconds. It is a further projectile in milliseconds for the frequency domain per subject. This time framework is constantly used on all the electrodes channels for a single subject. Signal AF3 has spectral power that ranges from 4100 to 4250 microvolts. Signal Pz has spectral power that ranges from 4155 to 4175 microvolts. Signal T7 has a spectral power that ranges from 4140 to 4180 microvolts. Signal T8 has spectral power that ranges from 4100 to 4250 microvolts.

Features are extracted based on the component spectral power, which is measured in microvolts' unit where the unnecessary components power is reduced based on dimensionality reduced algorithm as discussed above. After applying the model, a new visualization of the spectral power of all components is shown at an ELE state that results in the adjacent representation of the electrodes but has different spectral power. These electrodes signal include; AF4, AF3, Pz, T7, and T8 components. Signal AF4 has a spectral power that ranges from -100 to +100 microvolts with time series measured at 8000 milliseconds. This time framework is constantly used on all the electrodes channels for a single subject. Signal AF3 has a spectral power that ranges from -100 to +100 microvolts. Signal Pz has spectral power that ranges from -5 to +10 microvolts. Signal T7 has spectral power that ranges from -100 to +100 microvolts. Signal T8 has spectral power that ranges from -10 to +10 microvolts.

F. Classification

Classification is one of the major problems assigning one of N labels to an input signal which is newly generated, given labeled training data of inputs along with consequent output labels of them. To learn and recognize the EEG pattern, a machine learning algorithm is implied for classification which can be explained as a method for understanding the mapping or relation between EEG data classes against mental tasks such as a hand's movement [36]. Application of supervised learning is, however, a difficult task as the EEG data is noisy, and the selection of an optimum frequency band and evaluating a suitable set of characteristics are areas that still need to be solved. In addition, various degree of

attention influences the data quality, which then changes in their concentration.
Initially, the data set is recorded based on the delta, theta, alpha and beta, and gamma waves for each participant with 5 channel electrodes. For attention, two channels AF3 and AF4 data with beta (β) wave frequency [37] were extracted for further classification. Mean is calculated for each electrode from each participant's recorded data and calculate the average mean from each calculated mean of electrodes and this average mean have been utilized as labeled data for classification of an individual subject. Doing the same procedure, we have calculated all participants' average mean and finally, we have labeled the dataset with a multi-label data classification.

5. Results

We evaluated the SVM classifier by accuracy, precision, recall, and F-Measures rates. Figure 6 shows the confusion matrix, and the definitions of these performance measures are listed as follows:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\ Score = \frac{2*Precision*Recall}{Precision+Recall} \quad (4)$$

The scores were achieved through an SVM classifier using a linear kernel. The equation for prediction for a new input using the dot product between the input (t) and each support vector (ti) is calculated as follows:

$$f(x) = B(0) + sum(bi * (t,ti)) \quad (5)$$

Individual accuracy of participants was measured by breaking the dataset into 30% testing and 70% for training while for overall accuracy for creating the SVM model, all files were merged to make a single file and separate it with 30% of the data as testing and 70% for training. Support vector machine generates in total 8703 support vectors 4351 for attention class boundary and 4352 for inattention (which is labeled as "Distracted"), a class boundary that lies on this margin to separate attention and distracted classes with the cost of 0.1. Table 3 shows the confusion matrix of the e-learning environment through which precision, recall, and F-measure were calculated. The purple color shows the attention data and inside attention class red spots are misclassified data Furthermore, distracted data is represented by blue color and the misclassified data is also present in it which is shown as black spots as shown in Figure 5.

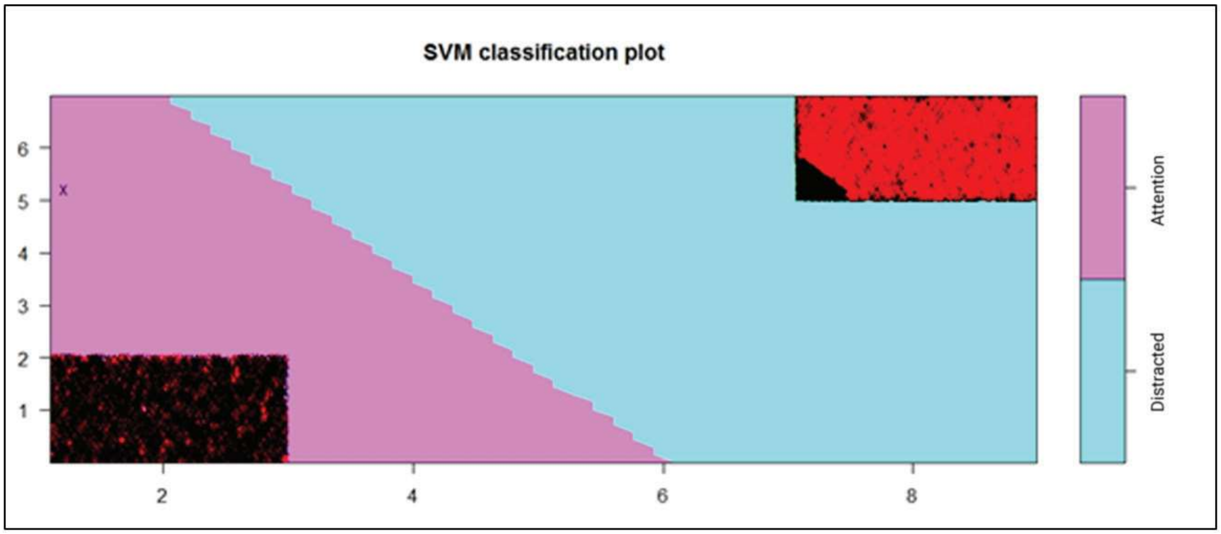

Figure 5: Attention level in e-learning environment support vectors

The value of cost (C) is large then the model chooses more data points as a support vector and thus it gets the higher variance and lowers bias, which may lead to the problem of overfitting.

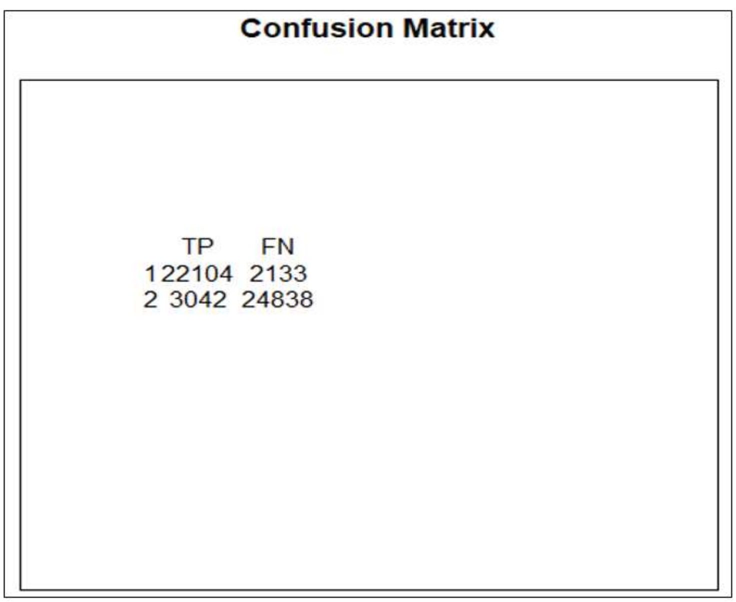

Figure 6: Confusion matrix E-learning environment

The overall accuracy shows the results of the SVM algorithm which is 90.07% with 0.879 precision, 0.911 recall, and 0.894 f-measure, and the mean of participant's data accuracy, precision, recall, and f-measure are 90.43%, 0.883, 0.897, and 0.890 respectively as shown in Table 4.

Table 4: E-learning environment results

	SUPPORT VECTOR MACHINES				
	Participants	Accuracy	Precision	Recall	F-Measure
E-LEARNING ENVIRONMENT	P1	90.25%	0.897	0.903	0.900
	P2	89.79%	0.884	0.895	0.889
	P3	91.46%	0.901	0.912	0.906
	P4	89.14%	0.881	0.894	0.887
	P5	90.94%	0.895	0.901	0.898
	P6	89.86%	0.899	0.895	0.897
	P7	89.43%	0.917	0.891	0.904
	P8	90.58%	0.874	0.891	0.882
	P9	91.89%	0.898	0.997	0.945
	P10	89.32%	0.842	0.855	0.848
	P11	90.43%	0.896	0.908	0.902
	P12	89.03%	0.789	0.881	0.832
	P13	91.56%	0.876	0.879	0.877
	P14	90.87%	0.897	0.884	0.890
	P15	91.86%	0.898	0.871	0.884
	Mean	90.43%	0.883	0.897	0.890
	SVM Model	90.07%	0.879	0.911	0.894

6. Conclusion

A Brain-Computer Interface (BCI), derived from the cognitive area of Human-Computer Interaction (HCI) is an efficient and successful emergent field [1]. The understanding is intended to explain the purpose through which the signals are produced. BCI is widely used as an integrated diagnostic tool to analyze brain signals and patterns by placing electrodes on the scalp. It gives real-time data. The EEG is used by BCI systems for monitoring and analyzing the signals of the human brain [3], [5]. Attention is an important term in educational settings. It is assessed by the cognitive mind by assisting the variety of inbound perceptual knowledge and preventing the external incentives managed by constrained cognitive minds for avoiding congestion [38], [39].

The proposed study focuses to evaluate the e-learning method and its efficiency by analyzing students' attention through EEG signals during the e-learning method and will evaluate the method if it is efficient for learning. The model was based on the following major steps to achieve the desired outcome: signal acquisition, noise (artifact) handling, pre-processing of data, and attention and cognitive load detection by feature extraction and classification. In the proposed approach, a learning model has been designed to assess attention in students, filtration of signals, and improve the accuracy of the BCI system. For recording signals, we used the EEG technique. EEG technique is commonly used for collecting data by the noninvasive method in which the participant wears the emotive insight headset.

The data was collected, and the learning model was designed to classify attention levels. Finite Impulse Response (FIR) filter was used to remove the noises that affect signals. Further independent component analysis (ICA) was applied to extract attention features from the noise-free signals. In the end, features were analyzed with EEG signals and tests of the participants in both environments. The Labeled training data is used to prepare the learning model and a Support Vector Machine (SVM) is used for classification. The experiment is based on attention analysis in learning, for these purposes, undergraduate students are selected for the experiment that generally studies in an e-learning environment. Acquiring a signal of participants generates the dataset. For this purpose, 15 participants were selected. EEG emotive headset is used on participants for signal acquisition.

The accuracy, precision, and recall for attention levels in an e-learning environment are achieved through the SVM classifier using a linear kernel. The individual accuracy of participants was measured by breaking the dataset into training and testing through the holdout technique, while for overall accuracy for creating the SVM model; all files were merged to make a single file. The efficiency of the SVM algorithm is 90.07% with 0.879 precision, 0.911 recall, and 0.894 f-measure. The overall accuracy also confines our hypothesis of better learning outcomes in the e-learning environment.

References

[1] Gu, X., Cao, Z., Jolfaei, A., Xu, P., Wu, D., Jung, T. P., & Lin, C. T. (2021). EEG-based brain-computer interfaces (BCIs): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications. IEEE/ACM transactions on computational biology and bioinformatics.

[2] Tenório, K., Pereira, E., Remigio, S., Costa, D., Oliveira, W., Dermeval, D., ... & Marques, L. B. (2021). Brain-imaging techniques in educational technologies: A systematic literature review. Education and Information Technologies, 1-30.

[3] Wang, H., Yan, F., Xu, T., Yin, H., Chen, P., Yue, H., ... & Bezerianos, A. (2021). Brain-Controlled Wheelchair Review: From Wet Electrode to Dry Electrode, From Single Modal to Hybrid Modal, From Synchronous to Asynchronous. IEEE Access, 9, 55920-55938.

[4] Nooreldeen, H., Badawy, S., & El-Brawany, M. A. (2021). EEG Signal Analysis Based Brain-Computer. Menoufia Journal of Electronic Engineering Research, 30(2), 34-38.

[5] Stefanidis, V., Anogiannakis, G., Evangelou, A., & Poulos, M. (2015). Stable EEG Features. In Optimization, Control, and Applications in the Information Age (pp. 349–357). Springer.

[6] Brumberg, J. S., Pitt, K. M., Mantie-Kozlowski, A., & Burnison, J. D. (2018). Brain-computer interfaces for augmentative and alternative communication: A tutorial. American Journal of Speech-Language Pathology, 27(1), 1–12.

[7] Vidal, J. J. (1973). Toward Direct Brain-Computer Communication. Annual Review of Biophysics and Bioengineering, 2(1), 157–180. https://doi.org/10.1146/annurev.bb.02.060173.001105

[8] Lebedev, M. A., & Nicolelis, M. A. (2017). Brain-machine interfaces: From basic science to neuroprostheses and neurorehabilitation. Physiological Reviews, 97(2), 767–837.

[9] Akyurek, E., & Afacan, O. (2013). Effects of Brain-Based Learning Approach on Students' Motivation and Attitudes Levels in Science Class. Online Submission, 3(1), 104–119.

[10] Joo, Y. J., Kim, N., & Kim, N. H. (2016). Factors predicting online university students' use of a mobile learning management system (m-LMS). Educational Technology Research and Development, 64(4), 611–630.

[11] Zhang, D., Zhao, J. L., Zhou, L., & Nunamaker Jr, J. F. (2004). Can e-learning replace classroom learning? Communications of the ACM, 47(5), 75–79.

[12] Lin, F.-R., & Kao, C.-M. (2018a). Mental effort detection using EEG data in E-learning contexts. Computers & Education, 122, 63–79. https://doi.org/10.1016/j.compedu.2018.03.020

[13] Li, Y., Li, X., Ratcliffe, M., Liu, L., Qi, Y., & Liu, Q. (2011). A real-time EEG-based BCI system for attention recognition in a ubiquitous environment. Proceedings of 2011 International Workshop on Ubiquitous Affective Awareness and Intelligent Interaction - UAAII '11, 33. https://doi.org/10.1145/2030092.2030099

[14] Nanda, P. P., Rout, A., Sahoo, R. K., & Sethi, S. (2017). Work-in-Progress: Analysis of Meditation and Attention Level of Human Brain. 2017 International Conference on Information Technology (ICIT), 46–49. https://doi.org/10.1109/ICIT.2017.53

[15] Liu, N.-H., Chiang, C.-Y., & Chu, H.-C. (2013). Recognizing the Degree of Human Attention Using EEG Signals from Mobile Sensors. Sensors, 13(8), 10273–10286. https://doi.org/10.3390/s130810273

[16] Ko, L.-W., Komarov, O., Hairston, W. D., Jung, T.-P., & Lin, C.-T. (2017). Sustained Attention in Real Classroom Settings: An EEG Study. Frontiers in Human Neuroscience, 11. https://doi.org/10.3389/fnhum.2017.00388

[17] Takeda, Y., Sato, T., Kimura, K., Komine, H., Akamatsu, M., & Sato, J. (2016). Electrophysiological evaluation of attention in drivers and passengers: Toward an understanding of drivers' attentional state in autonomous vehicles. Transportation Research Part F: Traffic Psychology and Behaviour, 42, 140–150. https://doi.org/10.1016/j.trf.2016.07.008

[18] Kuo, Y.-C., Chu, H.-C., & Tsai, M.-C. (2017). Effects of an integrated physiological signal-based attention-promoting and English listening system on students' learning performance and behavioral patterns. Computers in Human Behavior, 75, 218–227. https://doi.org/10.1016/j.chb.2017.05.017

[19] Ilgaz, H., Altun, A., & Aşkar, P. (2014). The effect of sustained attention level and contextual cueing on implicit memory performance for e-learning environments. Computers in Human Behavior, 39, 1–7. https://doi.org/10.1016/j.chb.2014.06.008

[20] Mendoza, J. S., Pody, B. C., Lee, S., Kim, M., & McDonough, I. M. (2018). The effect of cellphones on attention and learning: The influences of time, distraction, and nomophobia. Computers in Human Behavior, 86, 52–60. https://doi.org/10.1016/j.chb.2018.04.027

[21] Wang, C.-C., & Hsu, M.-C. (2014). An exploratory study using inexpensive electroencephalography (EEG) to understand flow experience in computer-based instruction. Information & Management, 51(7), 912–923. https://doi.org/10.1016/j.im.2014.05.010

[22] Lee, H, Kim, Y., & Park, C. (2018). Classification of Human Attention to Multimedia Lecture. 3.

[23] Hu, B., Li, X., Sun, S., & Ratcliffe, M. (2018). Attention Recognition in EEG-Based Affective Learning Research Using CFS+KNN Algorithm. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 15(1), 38–45. https://doi.org/10.1109/TCBB.2016.2616395

[24] Shen, Y. T., Chen, X. M., Lu, P. W., & Wu, J. C. (2018). Use BCI to Generate Attention-Based Metadata for the Assessment of Effective Learning Duration. In P. Zaphiris & A. Ioannou (Eds.), Learning and Collaboration Technologies. Learning and Teaching (Vol. 10925, pp. 407–417). Springer International Publishing. https://doi.org/10.1007/978-3-319-91152-6_31

[25] Lin, Y.-T., & Chen, C.-M. (2019). Improving the effectiveness of learners' review of video lectures by using an attention-based video lecture review mechanism based on brainwave signals. Interactive Learning Environments, 27(1), 86–102. https://doi.org/10.1080/10494820.2018.1451899

[26] Liao, C.-Y., Chen, R.-C., & Tai, S.-K. (2019). EVALUATING ATTENTION LEVEL ON MOOCS LEARNING BASED ON BRAINWAVES SIGNALS ANALYSIS. 13.

[27] Mert, A., & Akan, A. (2018). Emotion recognition from EEG signals by using multivariate empirical mode decomposition. Pattern Analysis and Applications, 21(1), 81–89. https://doi.org/10.1007/s10044-016-0567-6

[28] Abdulkader, S. N., Atia, A., & Mostafa, M.-S. M. (2015). Brain-computer interfacing: Applications and challenges. Egyptian Informatics Journal, 16(2), 213–230. https://doi.org/10.1016/j.eij.2015.06.002

[29] Tang, Z., Li, C., Sun, S. (2017). Single-trial EEG classification of motor imagery using deep convolutional neural networks. Optik-International Journal for Light and Electron Optics, 130, 11–18.

[30] Urigüen, J. A., & Garcia-Zapirain, B. (2015). EEG artifact removal—State-of-the-art and guidelines. Journal of Neural Engineering, 12(3), 031001.

[31] Rogasch, N. C., Thomson, R. H., Farzan, F., Fitzgibbon, B. M., Bailey, N. W., Hernandez-Pavon, J. C., Daskalakis, Z. J., & Fitzgerald, P. B. (2014). Removing artifacts from TMS-EEG recordings using independent component analysis: Importance for assessing prefrontal and motor cortex network properties. NeuroImage, 101, 425–439. https://doi.org/10.1016/j.neuroimage.2014.07.037

[32] Pruim, R. H. R., Mennes, M., van Rooij, D., Llera, A., Buitelaar, J. K., & Beckmann, C. F. (2015). ICA-AROMA: A robust ICA-based strategy for removing motion artifacts from fMRI data. NeuroImage, 112, 267–277. https://doi.org/10.1016/j.neuroimage.2015.02.064

[33] Yildiz, M., Bergil, E., & Oral, C. (2017). Comparison of different classification methods for the preictal stage detection in EEG signals.

[34] Sridhar, C., Bhat, S., Acharya, U. R., Adeli, H., & Bairy, G. M. (2017). Diagnosis of attention deficit hyperactivity disorder using imaging and signal processing techniques. Computers in Biology and Medicine, 88, 93–99. https://doi.org/10.1016/j.compbiomed.2017.07.009

[35] Wessel, J. R. (2018). Testing Multiple Psychological Processes for Common Neural Mechanisms Using EEG and Independent Component Analysis. Brain Topography, 31(1), 90–100. https://doi.org/10.1007/s10548-016-0483-5

[36] Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., & Yger, F. (2018). A review of classification algorithms for EEG-based brain-computer interfaces: A 10-year update. Journal of Neural Engineering, 15(3), 031005.

[37] Xu, J., & Zhong, B. (2018). Review on portable EEG technology in educational research. Computers in Human Behavior, 81, 340-349.

[38] Krauzlis, R. J., Bollimunta, A., Arcizet, F., & Wang, L. (2014). Attention is an effect, not a cause. Trends in Cognitive Sciences, 18(9), 457–464.

[39] Hommel, B., Chapman, C. S., Cisek, P., Neyedli, H. F., Song, J. H., & Welsh, T. N. (2019). No one knows what attention is. Attention, Perception, & Psychophysics, 81(7), 2288-2303.