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ENHANCING LEARNING ABILITIES IN STUDENTS USING A COGNITIVE NEUROSCIENCE MODEL BASED ON BRAIN-COMPUTER INTERFACE SIGNAL ANALYSIS

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Abstract. Computational intelligence is used to create artificially intelligent systems with the ability to learn, adapt, and solve problems. Learners' computational abilities can be improved with the help of Cognitive Neuroscience techniques. Computational intelligence refers to the ability of a learner based on the complex operations of the brain in the four relevant dimensions: Visual (V), Aural (A), Kinematic (K), and Reading/Writing (R/W). Our proposed framework consists of electroencephalogram (EEG) data acquisition, signal extraction, and EEG signal categorization to assess students' cognitive learning abilities. Our proposed approach uses an EEG device equipped with a microprocessor, a Think Gear (TGAM) EEG sensor, and a PCB of 16 dry electrodes. The EEG device and the remote processing device are connected by Bluetooth. The EEG signal provides the students with neurofeedback on their cognitive learning capability. The feedback obtained through the learning process will be endowing to improvise computational intelligence. The statistical derivative, Pearson Co-efficient, is used to find the correlation among the derived attributes. The attributes considered are the learner's gender, stream, age, and geographical region. The results obtained highlight that gender, stream, and age have no correlation with the detectable learning index, and the most accurate learners are kinesthetic ones. Bi-modal learners, who can maintain focus while reading and using their kinematic abilities, had the second-highest learning capacity.

Key words: Neurofeedback, Brain-Computer Interface, Cognitive Ability, Learning Index, Cognitive Neuroscience

1. Introduction. The ability of the human brain to grasp information, process it at a level of comprehension, and recollect it proficiently is what defines memory. Human cognition encompasses the psychological processes and procedures used in the collecting, organizing, retrieving, and utilization of information. Perception, attention, memory, language, reasoning, figuring out solutions, and making choices are just a few of the many mental activities that make up cognition [25]. The aptitude to retort to the problem solution is based on the knowledge consequent. The cognitive ability of learners can be enhanced by identifying their brain capacities' strengths and improving their retention process. To continuously acquire learning skills, the cognitive process needs to be developed. Human cognition is the capacity to transform short-term memory into a knowledge base. The concepts that map the brain-computer interface to human cognition are explained in detail in the following sections.

1.1. Human Cognition. The evolution of human cognition has been an interesting subject of research for decades. Humans are the only intelligent species that focus on thoughtfulness and extracting reasoning from the information acquired. The extraordinary cognitive abilities have evolved into a knowledge base in every aspect of our lives [42]. Millions of neurons exist in the brain, which excite and transmit information, particularly in the cognition phase.

In the teaching-learning environment, it is important to study the changes in cognitive ability while a learner is trying to attain some information and process it into knowledge. This research can be used to identify the cognitive developmental milestones that students reach at different cognitive stages as well as the factors that affect individual differences in cognitive development [31]. When intellectual abilities emerge in the brain, it is crucial to comprehend human cognition within a BCI (Brain Computer Interface) framework. The capacity from the neuron and the sympathetic function in relation to the cognitive abilities are passed down to current complex human abilities. These abilities include comprehending, remembering, evaluating, and understanding.

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1.2. Cognitive Skills. Cognitive science is the way to apprehend the working functions and behavioral aspects of human brains. To understand how the brain makes decisions to complete a task, cognitive science requires knowledge of a variety of fields, such as Computational Intelligence (CI), Neurofeedback (NF), and Artificial Intelligence (AI) [7]. Cognitive science pursues comprehending brainpower and conducting experiments to develop learning ability. During the learning phase, learners face difficulties that divert their focus from attaining knowledge [10]. Neurofeedback plays a vital role in reinforcing the ability of the learners to excerpt information.

Based on prior experience, the knowledge obtained will be adapted into a beneficial context. The process of collecting and deciphering sensory data from the environment is known as perception [12]. The ability to concentrate on a particular stimulus or activity while ignoring irrelevant information is referred to as attention. Capturing, preserving, and extracting information through time periods is the process of remembering. Making decisions and forming judgments based on memory is the process of reasoning. Cognitive abilities are the basic capacities of the human brain required for thinking, reading, learning, remembering, reasoning, and paying attention. Combined, they absorb data and contribute it to the body of knowledge people need for their daily lives, careers, and educational pursuits. Cognitive skills have a major role in how the brain interprets new information. This implies that if any of these abilities are compromised, the person's capacity to comprehend, retain, or apply the information will be impacted regardless of the type of material given to them. Most learning challenges are caused by one or more deficiencies in cognitive ability. By developing cognitive skills, students can use their brains to complete tasks, process information efficiently, and comprehend it. Intensifying cognitive skills can help learners perform better in almost every aspect of academics.

1.3. Bloom's Taxonomy for enhancing Cognitive skills. A system for classifying and organizing various levels of cognitive learning is called Bloom's Taxonomy [6]. Six degrees of cognitive learning that extend from lower-order to higher-order thinking abilities are included in the taxonomy:

- *Remembering:* At this stage, facts and definitions need to be remembered from memory.
- *Understanding:* This stage entails understanding the information's meaning, which could involve interpreting or summarising it.
- *Applying:* This phase involves applying the information to a new situation, such as using a concept to address a novel problem.
- *Analyzing:* This phase comprises breaking down the data into its individual elements and examining their relationships.
- *Assessing:* At this stage, decisions are made regarding the information, including its relevance and credibility.
- *Creating:* At this stage, data is utilized to generate a new idea, such as a product or a design that solves an issue.

These are six key cognitive-process classes, from the simplest to the most composite. When learners master evaluating, assessing, and creative skills, their cognitive abilities improve significantly. Bloom's taxonomy helps students pinpoint their areas for improvement, become more knowledgeable and proficient, and advance to a higher level of comprehension of the academic material [6]. When trained, the brain improves effectiveness and productivity by transferring information to knowledge [1]. Bloom's Taxonomy can be used to assess cognitive skills, which can also predict learning outcomes and academic achievement from acquiring strong skills [36]. Facilitators may utilize the taxonomy to create learning objectives, gauge student comprehension, and create tests and activities that foster higher-order thinking abilities.

1.4. Computational Cognitive Neurofeedback. Cognitive Neurofeedback draws renewed awareness as a process to self-regulate individual brain activity, which directly amends the core neural process of cognition. Neurofeedback is a type of biofeedback that helps people control their brain activities by monitoring brain waves and sending a feedback signal to the subject [5]. The audio and/or video feedback is typically provided using neurofeedback. Positive or negative feedback is generated for favorable or undesired brain actions. The learners can utilize this technique as a method for cognitive enhancement [29] [27]. In this paper, we have presented a neurofeedback framework conversing significant features applicable to the collection of electroencephalography (EEG) signals. The elements pertinent to a practical comprehension of neurofeedback for identifying learning styles are considered for designing this framework. All the practical concerns regarding evaluating learning styles

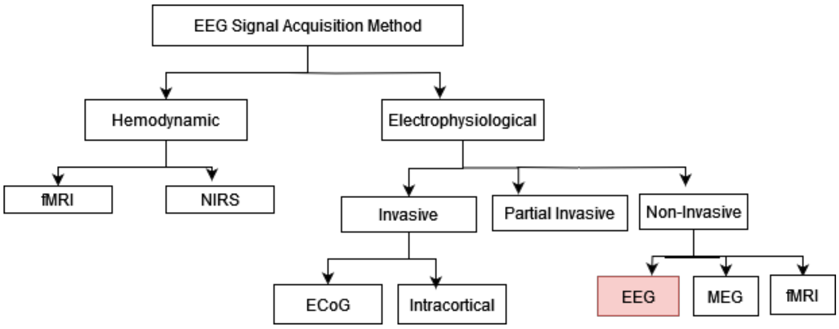


Fig. 1.1: BCI Signal Acquisition Methods

are demonstrated for improved learning skills using neurofeedback. The results also show improved academic skills through frontal beta waves. Neurofeedback supports volitional regulator brain activity using non-invasive recordings. The learning ability gets reinforced subconsciously by changing the brain wave excitation. By generating electrical movement over a procedure of extent and strengthening, the brain absorbs to administer and achieve higher concentration levels. Cognitive neuroscience enables learners to comprehend how their brains function for decision-making, awareness, thought processes, and behavior.

1.5. Brain-Computer Interface. A direct communication channel between the brain and a computer or other external devices is made possible via Brain-computer Interfaces (BCI) [12]. They have potential uses in various domains, including rehabilitation, affective computing, robotics, gaming, and neuroscience, and they provide a greater degree of flexibility by enhancing or replacing human peripheral functioning capability. A brain-computer interface (BCI) is a computer system that gathers, analyzes, and translates brain signals into commands that are transmitted to an output device to carry out a desired action. Therefore, BCIs do not use the brain's usual output channels, which are peripheral nerves and muscles. The term "BCI" describes equipment that uses and monitors signals produced by the Central Nervous System (CNS). EEG equipment can be used to provide an interface between a computer and the human brain. An EEG machine captures brain waves without generating an output that modifies the user's surroundings. The signal is acquired by placing sensors (electrodes) that read the amplified electric charge [40]. The brain neurons excite, producing a small amount of electric current that is amplified and collected through the electrodes using a noninvasive method as described in Fig.1.1. This work projects the use of the invasive method under electrophysiological activity. Spontaneous signals are gathered through BCI to study EEG patterns connected with the cognitive features of brain mapping [37]. For BCI applications, signals can be acquired using a variety of techniques, such as:

- *EEG:* EEG is the most popular technique for gathering signals for BCI applications. EEG electrodes are applied to the scalp to assess the brain's electrical impulses. Signal processing and relevant characteristics are extracted and used to operate the computer or other external devices.
- *fMRI:* Functional Magnetic Resonance Imaging (fMRI) analyses changes in brain blood flow using radio waves and a magnetic field. These modifications are used to infer brain activity and for BCI applications.
- *Electrocorticography (ECoG):* Electrodes are positioned on the outermost layer of the brain to record electrical activity. Compared to EEG, this method offers a higher spatial resolution when used in research and therapeutic contexts.
- *Magnetoencephalography (MEG):* MEG is the process for determining the magnetic fields generated by brain electrical activity. This technique is applied in research settings and offers excellent temporal and geographical resolution.
- *Near-Infrared Spectroscopy (NIRS):* NIRS analyzes variations in the brain's blood's oxygen and carbon dioxide levels. The approach can be applied in real-life situations and is non-invasive.

Fig.1.1 depicts different methods used to acquire the brain signals.

1.6. Research Contributions. To improve adaptivity in e-learning systems, this study explores the potential of NeuroSky's Mindset headset as a non-invasive technique for monitoring attention and meditation levels. Incorporating Brain-Computing Interface (BCI) assessments into an e-learning environment allows tracking variations in learners' preferred perceptual learning modalities, which are classified according to the VARK model (Visual, Auditory, Read/Write, and Kinesthetic). The following comprise the research contributions of this paper:

- A pioneering cognitive neuroscience model that leverages BCI signal analysis to enhance learning abilities in students. This model offers a novel pathway toward optimizing educational outcomes by integrating neuroscience principles with technology.
- With the awareness of each student's distinct brain patterns, teachers can facilitate their lesson plans and content delivery techniques to optimize learning outcomes and foster a more productive and diverse learning environment.
- Clustering algorithms are deployed to identify similar trends and preferences among students by organizing them into discrete clusters based on comparable learning characteristics.

2. Related Work. Cognitive ability, which includes functions like attention, memory, and reasoning ability, refers to the capacity of the human brain to process, store, and retrieve information. It is currently one of the most researched and stable determinants of academic performance. This section discusses the evolution of the application of brain signals to identify individuals' learning styles.

Acquisition of brain signals solves the challenge of perceiving what actually exists in the brain. The acquisition of the signals, interpretation, and analysis of the signals affect the derivation of the learning ability of the user [34]. Signal acquisition prompts complex processes in some of the brain areas. An indigenous current is engendered when neurons are elicited. The potential difference is amplified and collected as EEG waves. These signals are produced during the synaptic movement of the dendrites in the brain's cerebral cortex, as suggested in [2]. The membrane potential directed in the direction and inflated through channels entails mostly sodium, potassium, calcium, and chlorine ions [37]. According to the authors of [39], a BCI machine that performs pattern recognition and signal processing can infer signal activity from the brain. As per the work proposed in [30], BCI can be seen as a communication scheme expediting individuals to connect with their environments during the segment where the operation of peripheral nerves and muscles does not transpire.

Researchers in [41] proved that BCI constructs a different strategy of connecting an individual's brain signals to peripheral devices such as computers, synthesizers, and assertive appliances by accessing the sensory-motor nerves channel for relaying the brain signals. As discussed in [28], cognitive neuroscience improves academic performance by predicting the impact on learning styles. A range of neuropsychological tests and training are used to assess cognitive function in patients with brain injuries while they are receiving treatment. However, considering the typical problems that patients have, problems with ecological validity arise. As per the research presented in [14], a spatial memory task may be incorporated into any virtual environment and has good ecological validity. For the purpose of performing trials to uncover cognitive impairments by personalizing surroundings and target objects for each user, both healthy individuals and those with brain injuries were taken into consideration.

In [38], a game-based approach is suggested to assess and improve cognitive abilities. The characters in the game use varying positions to evaluate the players' attentiveness. If the learner's attention is diverted, the game exits, making the player pay full attention. A significant improvement was observed in learning abilities through such cognitive games. The work in [46] delves into nine well-known effects, three from each of the areas of perception/action, memory, and language — and discovers that they are quite dependable. They can be replicated not only in online settings but also with non-native participants without the effect size being diminished. This work concluded that some cognitive tasks are sufficiently constrained to capture behavior from outside influences, such as the testing environment and recent prior experience with the experiment, to produce extremely robust effects.

The learning style is a conventional communication style that monitors and articulates the information and builds behavioral patterns. The lead to determining the learning styles in a classroom setting can predict the available data into meaningful information for customization of learning. When a facilitator is teaching, accessing learning styles is challenging and competitive. Learning styles reflect how learners accept and choose

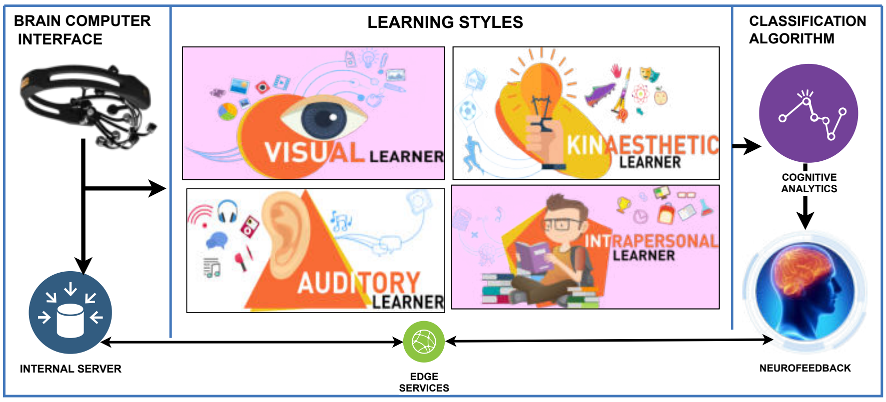


Fig. 3.1: Proposed Framework for Human Cognition Assessment through BCI

to comprehend, establish, and replicate the content. Cognitive psychology outlines learners' variances in the attainment of knowledge and their impression of the content and retrieval of information. Ultimate wisdom for beginners contrasts understanding, viewpoint, and alertness in the present scenario and is described in the association of intellectual senses. The detectable learning index is the pattern the learner inhibits while acquiring content. The learning index demonstrates the ideal way for beginners to obtain proper knowledge. Technically, an individual's learning style is a distinct way through which the learners understand the attention techniques and embrace the content. It is essential to find digital markers for the attention span of the learners to understand their learning behavior.

Table 2.1 provides the summary of the existing work in the domain of identification of people's learning styles using BCI. This summary highlights the input and statistical methods utilized by various studies, the Machine Learning (ML) or Deep Learning (DL) models employed, evaluation metrics, and the learning styles considered for the study. This table also compares our proposed approach with the existing ones and shows how it differs regarding the parameters mentioned above.

3. Proposed Framework. Our proposed framework consists of a model to identify a learner's learning style by acquiring EEG signals from the brain. As shown in Fig.3.1, the framework is implemented in two phases. The first phase involves the acquisition of brain signals, followed by a phase that determines the user's learning ability. The outcome generated by the first phase is provided as input to the subsequent phase.

The activities associated with both phases of our proposed framework are as follows:

- **Phase 1:** This phase is responsible for collecting the brain signals to evaluate the learners' cognitive abilities.
- **Phase 2:** Based on the acquired brain signals in the first phase, this phase attempts to decipher the learning abilities by computing the DLI (Detectable Learning Index). This index is essential to determine the attention span of learners as well as to obtain Neurofeedback from them. Learning styles are identified for each subject based on the processing involved in this phase.

The application scenario in our framework is a complete method for obtaining and analyzing electroencephalography (EEG) signals straight from the brain to determine each learner's distinct learning style. Enhancing student performance and cognitive development can be achieved by fostering more effective and engaged educational experiences through an understanding of and accommodation for varied learning styles.

3.1. Learning Styles. As per the VARK model of learning, different learning styles for learners are depicted in Fig.3.2. Most subjects follow any one or more of the following learning styles: Visual (V), Aural or Auditory (A), Reading/Writing (R/W), and Kinesthetic (K). The fundamental characteristics of learners having different learning styles are discussed below:

- *Visual (V):* As their name implies, visual learners retain information better when they see it. They like information to be presented in an eye-catching way. This type of learning usually involves paying great

Table 2.1: Analysis of the Existing BCI-based Solutions for Improving Learning Abilities

Paper	**Input Method**	**Statistical Method**	**ML/DL Model**	**Performance Metrics**	**Learning Style**
[45]	EEG Signals	Power Spectral Density (PSD)	Clustering Algorithm	Not Mentioned	Stable, Adaptive, Changeful
[32]	Chatbot Interactions (Textual Data), Brain Waves (EEG Signals)	Word2Vec, Bag-of-N grams, Short-Time Fourier Transforms (STFT)	CNN	Precision: 95%, Accuracy: 93%, F1-Score: 93%	-
[8]	-	Split Validation Accuracy Test	K-Means, X-Means, K-Medoids	Davies-Bouldin Index (DBI) values: K-Means, X-Means, K-Medoids	VARK
[43]	EEG Signals	-	SVM, Backpropagation Neural Networks, 1-DCNN	Accuracy: 71.2%	VARK
[20]	-	Correlational	SVM, K-NN	Precision, Recall, Accuracy	VARK
[26]	Chatbot, EEG Signals	-	Naive Bayes, Decision Tree	Accuracy	VARK
[35]	User-Queries, NLP	Rule-Based Models, Data-Driven Models	Naive Bayes, N48, Canopy, Retrieval-Based, Generation-Based Models	Accuracy	VARK
[44]	EEG Signals, ILS, Online Behaviour Analysis	Pearson Statistic	SVM, K-NN, Bayesian Network, CNN, RNN, Hybrid Network Architectures	Accuracy	VARK
[33]	-	Regression based	Decision Tree	Single-Modal Learning Style: 100% Accuracy for Prediction; Multi-Modal Learning Style: 83.5% Accuracy for Prediction	VARK
[15]	Adaptive Content, Adaptive Assessment	Moodle LMS	-	Better Results in Listening, Reading, Speaking, Writing	VARK
Proposed Approach	EEG Signals	Pearson Co-Efficient	Clustering	Silhouette Score and Davis-Bouldin Index	VARK, Multi-modal

attention to details and nonverbal cues, as well as mentally imagining scenarios to help with knowledge processing.

- *Aural (A):* Information is frequently retained more easily by auditory (or aural) learners when it is heard. Rather than actively engaging in class or taking notes, they usually find it easier to listen to others explain the information and can usually regurgitate it back to them.
- *Reading/Writing (R/W):* When new knowledge is delivered in the form of words and text, those who favor reading and/or writing as their preferred learning styles usually retain it the best. They like

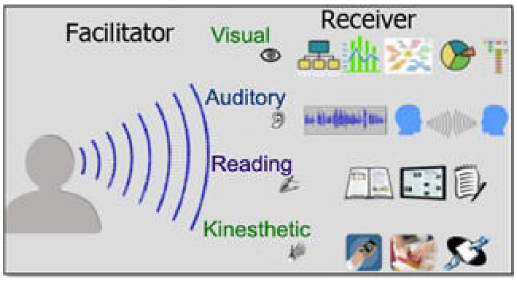


Fig. 3.2: Learning Style Classification (VARK)

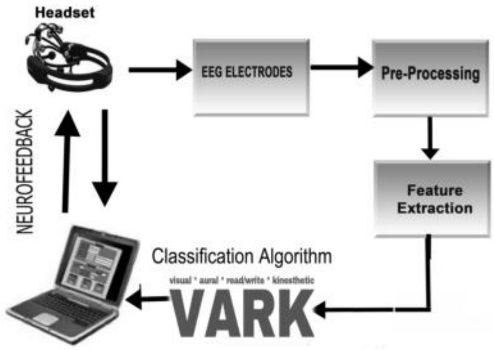


Fig. 3.3: Workflow of the Proposed Framework

reading definitions, compiling information into lists, and synthesizing it in ways that make the most sense to them.

- *Kinesthetic (K):* Kinesthetic learners acquire knowledge through "trial and error" methods. Therefore, for them, practical experience is essential. To better understand how things work, they like to work out physically and handle things directly.
- *Multimodal (M):* Some learners don't have any strong preferences when it comes to learning styles. They adjust to the requested or in-use style as they learn. Typically, multimodal preferences are VARK combinations. Using more than one of the above-mentioned learning styles is necessary. Any two learning styles, for instance, Visual and Kinesthetic (VK), can be combined to create a bimodal VARK style. Any three learning styles can be combined to create a trimodal VARK style. For example, consider a trimodal combination of Kinesthetic, Read/Write, and Aural (ARK). Some individuals with multimodal learning styles find that learning and communicating need the use of multiple styles. Using just one learning style makes them feel insecure.

3.2. Identification of Learning Styles. To identify a person's learning style, our proposed framework implements four major processes that are mapped with the two phases, as discussed previously. The list of these processes is as follows:

1. Extracting cognitive signals through EEG
2. Pre-processing EEG signals
3. Feature Extraction from pre-processed signals
4. Categorization of signals using Clustering

These processes are depicted in Fig.3.3 and described in the following subsections.

3.2.1. Extracting Cognitive Signals through EEG. Dynamic activity in the brain involves neural arrangement processing and circulation of neural activity. The chemical changes in the brain's grey matter indicate cognition, which occurs during the excitation of neurons [18]. The potential of neuroscience is to find the relation between the external activity taking place and the effect of the same on the neuron information. The information is processed in the brain trails while executing cognitive tasks such as understanding, interpreting, and analyzing.

The cognitive data can be collected using different methodologies like placing dry electrodes or wet electrodes on the scalp [3] [17] [9]. Such non-invasive methods are usually used for academic tracking purposes. Depending on the chemical and electrical changes occurring in the brain, cognition processes like perception, memorization, understanding, developing insights, and reasoning are evaluated. Learner attention is often stimulated by playing cognitive games that require full attention while using BCI devices.

In the proposed framework, EEG signals are acquired from the headset that has three dry electrodes. These electrodes are positioned on the forehead of the subject and used to send or collect the amplifying signals. In this case, these electrodes serve as a touching base point for the reference electrode placed at the ear lobe. A microcontroller connected with these electrodes via Bluetooth acquires and interprets the signals.

The EEG equipment is connected to a computer via Think Gear software. The appropriate functions corresponding to the supplement of the instinctive mind are distinguished by a headset complemented by the NeuroSky Think Gear sensor. It spurts as a backdrop procedure progressively charging a wide computer system outlet through granting requests from the other domain to join. The solicitations accumulate instructions from the associated Think Gear.

3.2.2. Pre-processing of EEG Signals. In order to collect and process brain signals, modern BCI technology makes use of wireless headphones as well as portable interfaces and processing equipment. The degree to which subjects are able to comprehend the material is determined by their spatial memory recall dimension. BCI technology, which uses hardware and software-based communication systems to enable humans to interact with their surroundings without using peripheral nerves or muscle inputs by using control signals produced from EEG activity, is widely used to measure spatial memory. It is based on the calibration of electrical signals that reflect and measure different types of brain activity.

When a brain is actively engaged or paying attention, it emits a signal that is known as an ”attention signature.” In the learning environment, a facilitator/teacher needs to understand students’ learning styles that are directly proportional to their attention signatures.

The headset continuously analyses the data, producing alpha, beta, and other waveforms that are output to the EEG power spectrum. In addition to the eye blink, values for attention and meditation are recorded. The artifacts are removed, and the concentration focus is interpreted in the sale of 1-100. The acquired values are split into three thresholds; the range 0–20 is classified as being below the attention span threshold. The range of improvement in achieving focus is defined as being between 20 and 40. Range values of 40–60 are regarded as unbiased. High attention value values are defined as those with a measurement above 60.

3.2.3. Feature Extraction. The input data acquires features of the frequency domain, such as head movement, eye blinking, and alpha, beta, gamma, and theta waves. Beta waves are the EEG signals associated with cognition. To distinguish between the normal and abnormal waves in EEG signals, feature extraction is applied using Principal Component Analysis (PCA) and Blind Source Separations (BSS) [16] [22]. Since beta waves indicate a learner’s attention and focus, acquired signals must be categorized into distinct thresholds according to the standard frequency to determine cognitive development [23].

The feature vector has been trimmed to reduce the complexity of the feature extraction process without sacrificing any pertinent information. Therefore, optimal discrimination features are essential for deciphering the learner’s learning style pattern and practically recognizing various patterns.

3.2.4. Categorization of Signals through Clustering. This stage aims to identify the subject’s learning style by classifying their brain signals into different categories based on the pre-determined range of frequencies. Table 3.1 shows the brain signals with their frequency ranges. This table and Fig.3.4 depict that each frequency range corresponds to a specific category of brain waves and particular types of activities. Based on this frequency range specification, the acquired EEG signals are categorized as Delta, Alpha, Gamma, Beta, and Theta.

Every brain signal has a state of mind linked with it, and there are two categories for every frequency, such

Table 3.1: Frequency Range of Brain Signals

Brain Signal Category	Frequency Range
Alpha	8 - 13 Hz
Beta	14 - 30 Hz
Delta	$<$ 3.5 Hz
Gamma	30 - 100 Hz
Theta	4 - 7 Hz

Table 3.2: States of Mind associated with different types of Brain Signals

State of Mind	Brain Signal Category
Relaxation (Meditating/Daydreaming/Mental Readiness)	Alpha
Alert (Engaged in learning/problem-solving/mentally challenging tasks)	Beta
Sleep (Dreaming/Deep Sleep)	Delta
Anxiety (Depression, Stress)	Gamma
Deep Relaxation (light sleep/drifting off to sleep)	Theta

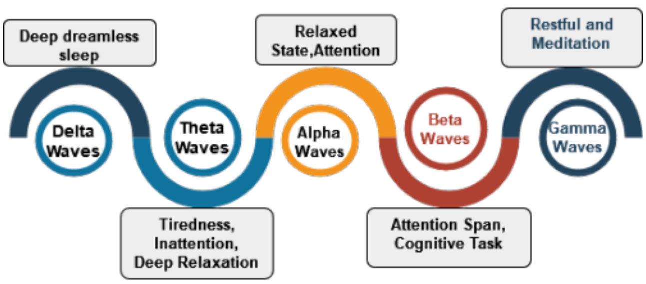


Fig. 3.4: Classification of Brain Signals

as spikes and field potential [25]. Based on this, the brain distinguishes between various forms of learning styles. From Table 3.2, it is evident that learning and maintaining high concentration cause beta waves to be produced. Here, we use the Detectable Learning Index (LI) to determine the learning style based on the frequencies of beta waves. In our experimental setup, the participants were given different types of activities that generated beta waves. Different clustering methods were then used to identify individuals' learning style preferences.

3.3. Proposed Algorithm. The algorithm followed by our proposed framework consists of a total of 7 steps. The exact sequence of these steps is explained below and depicted in Fig.3.5:

Step 1: The BCI data signals are collected through wearable headsets.

Step 2: The signals are converted into the CSV format by excluding artifacts like eye-blink and head movement through signal pre-processing techniques.

Step 3: X is the variable to check whether the headset's connection is established; the value of X is assigned as 1 if the connection is established.

Step 4: The signals are further classified as "Beta waves," signifying attention span and cognitive ability.

Step 5: The signals are recorded with a notation of a special number delegated to the learner to avoid demographic details.

Step 6: The signals are collected at a span of 1 second, the recorded signals are obtained for the planned time, and the software will store the signals in CSV format.

Step 7: Check the value of X. If X is 1, repeat the entire process. End the data collection process if X

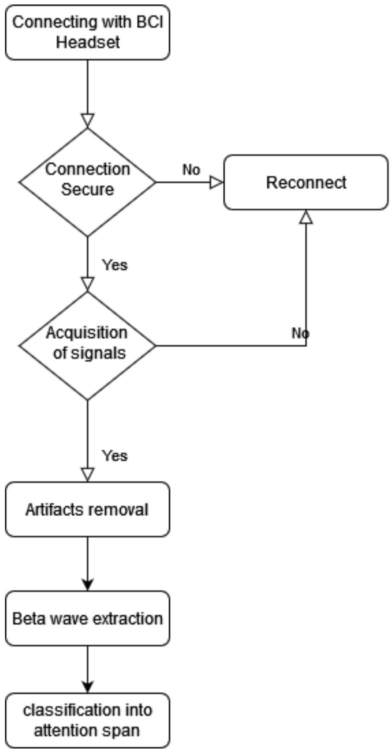


Fig. 3.5: Proposed Algorithm

changes or the connection is lost.

4. Results and Discussions. After the EEG signals are categorized, an analysis is conducted to see how Bloom's taxonomy and Kolb's [19] observable learning styles relate to one another. It is widely recognized that Kolb's learning style model can help improve performance, particularly in higher education. Kolb proposed the idea that individuals have varying preferences regarding learning methods. The choice of learning style is determined by combining two distinct learning styles. This section discusses the experimentation-related details and results obtained. Performance analysis is also presented in this section.

4.1. Experimental Setup. The main objective of our work is to determine how students' academic performance improves when they can reason, apply, and create in the higher order of Bloom's taxonomy when they are aware of their capacity for learning. The statistics clearly state that learners mostly furnish their learning styles in the prime years of education. Modifications of teaching strategies that involve both intellectual and practical learning should be considered to meet the needs of students.

Our experiment involved 280 healthy students from an educational institute in Gujarat, India. These undergraduate students were enrolled in a technical course in the domain of computer engineering and participated voluntarily in this study. The participants were aged 18 to 25. Out of 280 students, 168 were male, and 112 were female. The Gujarat region was divided into three subregions: North Gujarat, South Gujarat, and Middle Gujarat. Regional data was collected to check if it impacted the participants' attention levels or learning styles.

The Neorosky EEG sensor was placed at the forehead of the participants. The experiment was conducted in a quiet setting without any noise. Before being permitted to record their brain EEG signals, participants were instructed to take deep breaths and calm themselves down. Then, the participants were provided with different kinds of content, including visual images or pictorial data, aural or audio recordings, a manuscript for reading, and puzzles to solve. While going through the provided visual, aural, reading/writing, or kinematic

Table 4.1: Clustering Methods

Clustering Method	Number of Clusters	Learning Style
DBSCAN	3	V, A, K
Simple K-Means	4	V, A, K, M
Hierarchical	4	V, A, K, M

content, participants continually produce Beta waves at one-second intervals for two minutes.

Using the NeuroSky EEG headset, the brain waves were recorded for a total of 122 seconds. Here, the first and last seconds were used to begin and end the recording of EEG signals. The collected signals database comprised 34160 entries, 280 rows representing the participants, and 122 columns representing seconds.

During the experimentation, it was found that every participant generated a unique EEG brain wave. The EEG brain waves collected through EEG sensors varied largely. Hence, the normalization of EEG brain signals was performed prior to their classification. The amplitude of Beta waves was higher in response to the provided visual, aural, reading/writing, or kinematic learning material based on the preferred learning style of the participant. Based on such patterns, our proposed framework categorized learners as visual (V), aural (A), strong readers (R), kinematic (K), or multimodal (M). During our testing period, visual learners produced a higher range of Beta waves when they were presented with pictorial data or visual images. Auditory learners responded with high Beta waves when they listened to audio recordings. Strong readers produced high amplitude for Beta waves when they were given a manuscript to read. The frequency of Beta waves was higher when kinematic learners attempted to solve the given puzzles. A few learners showed high Beta waves for more than one type of content; hence, they were identified as multimodal learners. Some visualizations of brain signals generated from the NeuroSky EEG headset are presented in Fig.4.1 for different categories of learning styles.

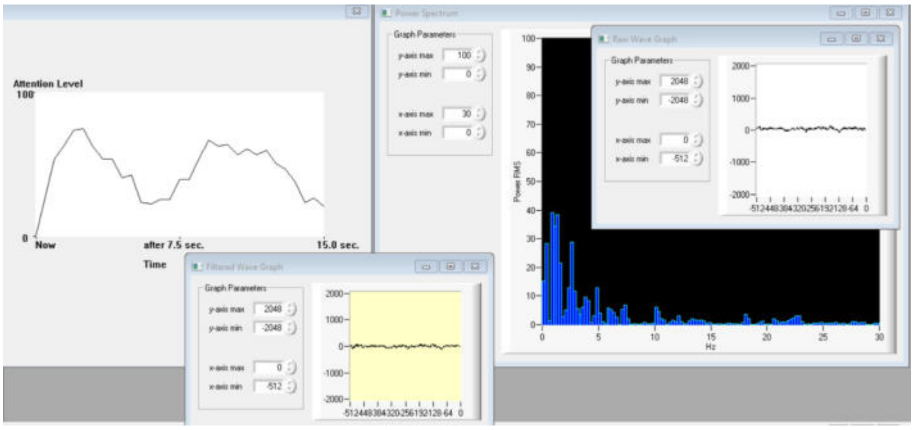
4.2. Clustering for Classification. Clustering is an essential tool for classification problems because it enables preprocessing and feature engineering. We applied three popular clustering algorithms to group participants into clusters based on their respective learning styles: K-means Clustering, DBSCAN Clustering, and Hierarchical Clustering. Participants were divided into four clusters: Cluster 1 for visual learners, Cluster 2 for auditory learners, Cluster 3 for kinesthetic learners, and Cluster 4 for multimodal learners. Table 4.1 represents the clustering methods employed, the number of clusters generated, and the corresponding learning style for the three clustering algorithms.

4.2.1. K-means Clustering. K-means clustering [13] is one of the most commonly employed unsupervised machine learning algorithms for grouping data points into clusters or groups according to similarity. For clustering learners based on their preferred style of learning, the following steps were used to perform K-means clustering:

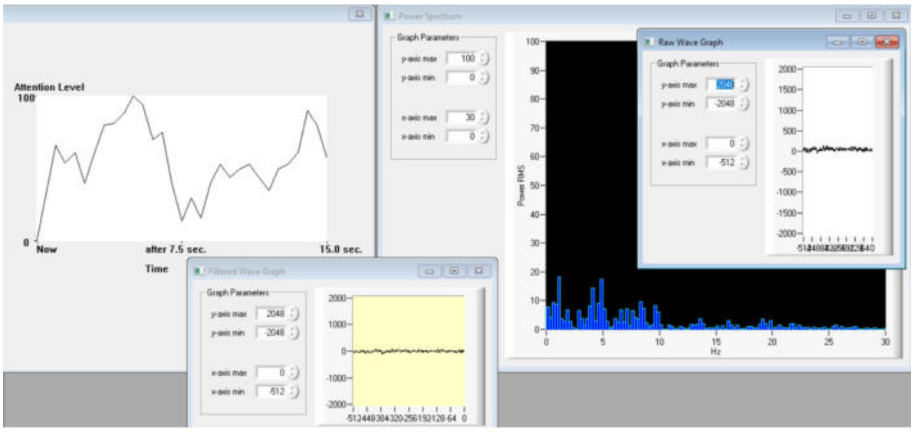
- Choose K data points at random as the initial cluster centroids from the dataset.
- Using Euclidean distance, assign each data point to the cluster whose centroid is closest to it.
- Recalculate the cluster centroids using the average of the data points allocated to each cluster.
- Repeat the assignment and centroid update processes until convergence (when the centroids no longer vary appreciably or a predetermined number of iterations is reached).

Fig.4.2 presents the visualization of the clustering performed by the K-means clustering algorithm. The centroids, represented by points in red at coordinates (centroids[:, 0], centroids[:, 1]), are overlaid on the plot. The data points (X[:, 0], X[:, 1]) are colored according to their respective clusters, with each cluster corresponding to one of the following learning style preferences: Visual, Audio, Kinesthetic, and Multimodal. Table 4.2 shows the confusion matrix for the K-means clustering. There are four clusters considered here. Learning Styles included in this algorithm are four, namely auditory (A), kinesthetic (K), visual (V), and multimodal (M). Participants exhibiting a specific learning style are assigned to the corresponding clusters.

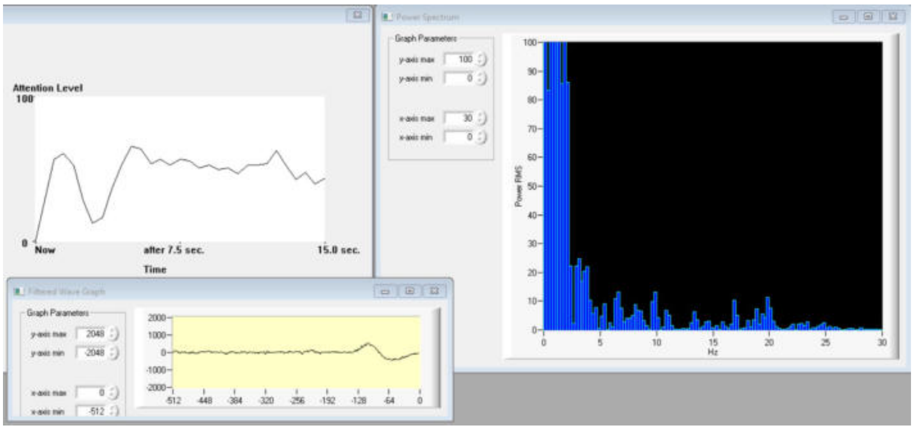
4.2.2. DBSCAN Clustering. The widely-used clustering technique DBSCAN (Density-Based Spatial Clustering of Applications with Noise) [11] is used in machine learning to find clusters in a dataset that vary



(a) Aural



(b) Visual



(c) Multimodal

Fig. 4.1: Visualization of Brain Waves for Visual, Aural, and Multimodal Learning Styles

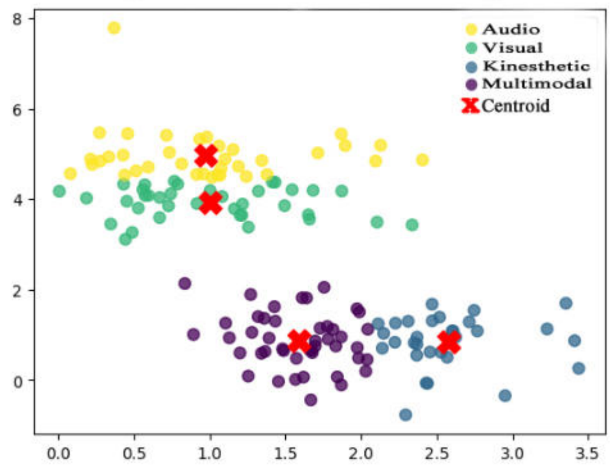


Fig. 4.2: Visual Representation of K-means Clustering

Table 4.2: Confusion Matrix for K-means Clustering

	Cluster Number				
Learning Style	0	1	2	3	**Total**
K	41	15	0	28	84
A	0	36	0	35	71
V	34	0	27	22	83
M	14	11	0	15	40
Total	89	62	27	100	

in size and shape. This clustering algorithm can detect clusters of arbitrary shape or size without having prior knowledge of the number of clusters. In our experiment, the following steps were followed to apply DBSCAN clustering:

- Choose a data point at random.
- Recursively build a cluster by adding all reachable core points to it for each core point or boundary point that hasn't been allocated to a cluster yet.
- A cluster comprises all the points that can be accessed from a central location. Noise is defined as any unassigned points that remain.

Fig.4.3 illustrates the result of DBSCAN clustering algorithm. The confusion matrix for the DBSCAN clustering is shown in Table 4.3. Each item in the matrix denotes the number of instances the algorithm assigned to a specific cluster. The numbers 0, 1, and 2 designate the clusters. The table's rows correspond to the four learning styles — auditory (A), kinesthetic (K), visual (V), and multimodal (M). The columns of the table correspond to the various clusters. There are 70 instances when the DBSCAN approach has resulted in an inaccurate clustering. In Cluster 0, there are 37 outlier data; in Cluster 1, there are 2 outlier data; and in Cluster 2, there are 24 outlier data.

4.2.3. Hierarchical Clustering. Another popular clustering technique for hierarchically grouping related data points is hierarchical clustering [21]. The steps that were used to implement the hierarchical clustering algorithm for our experimentation are listed below:

- Assign every data point a cluster of its own. Every data point is first regarded as a singleton cluster.
- Determine the distance or similarity between every two clusters.
- Using the selected distance or similarity measure, identify the two nearest clusters.

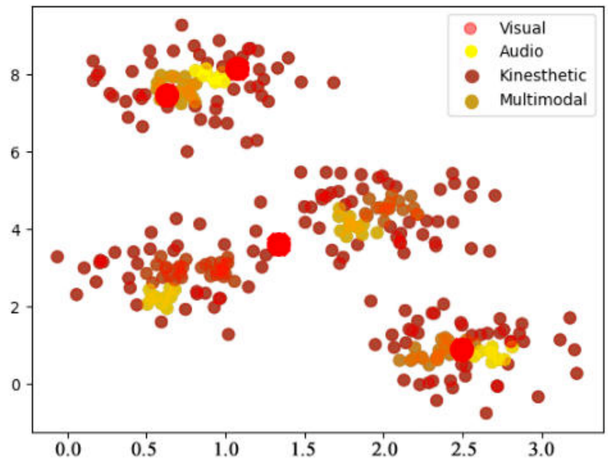


Fig. 4.3: Visual Representation of DBSCAN Clustering

Table 4.3: Confusion Matrix for DBSCAN Clustering

	Cluster Number			
Learning Style	0	1	2	**Total**
K	44	0	18	62
A	0	0	29	29
V	27	30	0	57
M	14	5	6	25
Total	85	35	47	

Table 4.4: Confusion Matrix for Hierarchical Clustering

	Cluster Number				
Learning Style	0	1	2	3	**Total**
K	26	0	0	36	62
A	0	29	0	0	29
V	8	0	49	0	57
M	11	12	0	0	23
Total	45	41	49	36	

- Determine the new cluster's distances and similarities to every other cluster again.
- Until there is just one cluster left, or until there are four clusters total, keep merging the nearest clusters and updating the distance matrix.

The number of clusters for this algorithm is four. These clusters are labeled as clusters 0, 1, 2, and 3. Four learning styles are considered here. Auditory (A), kinesthetic (K), visual (V), and multimodal (M) are learning styles for which the clusters are formed. The performance of the Hierarchical clustering is found to be almost similar to the performance of the DBSCAN algorithm. The visual representation of the hierarchical clustering is depicted in Fig.4.4. Table 4.4 represents the confusion matrix for the hierarchical clustering.

4.2.4. Performance Evaluation. By comparing an object's similarity to its own cluster to that of other clusters, a silhouette score is a technique for evaluating the quality of clusters created by a particular algorithm [4]. Every data point is given a silhouette coefficient, with values ranging from -1 to 1. An object is well-matched

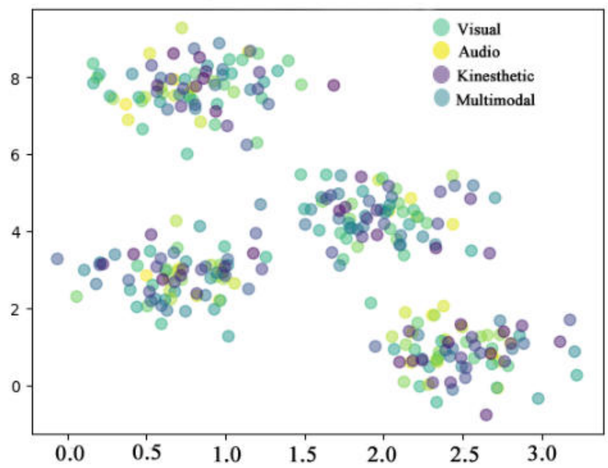


Fig. 4.4: Visual Representation of Hierarchical Clustering

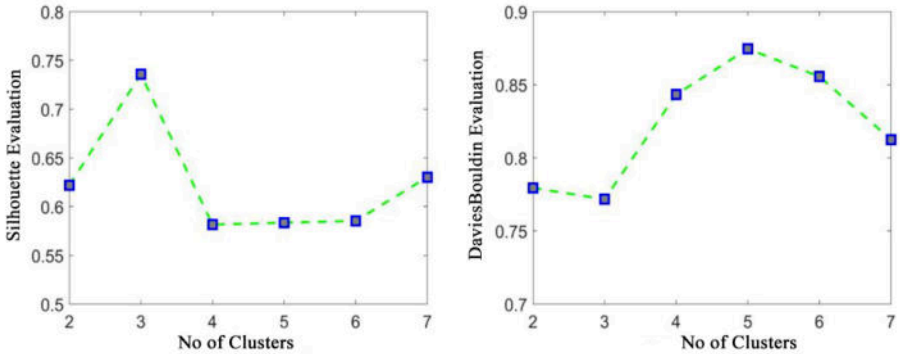


Fig. 4.5: Comparision of Silhouette Score and Davis-Bouldin Index

to its own cluster if its silhouette coefficient is high and poorly matched to neighboring clusters if it is low.

Another matrix for evaluating cluster quality is the Davis-Bouldin index [4]. It serves as a criterion for selecting and validating clusters. The average distance between each cluster point and its centroid is determined for each cluster using the Davis-Bouldin index. Additionally, it calculates how similar each pair of clusters' centroids are to one another. The ratio of within-cluster dispersion to between-cluster similarities is averaged to get the index.

Both these metrics are essential for assessing and improving clustering results, providing the opportunity to decide which clustering algorithms are most appropriate and effective for the given scenario. The outcome of both these metrics are shown in Fig.4.5. Better clustering quality is indicated by lower values for the Davis-Bouldin index, whereas higher values indicate poor clustering quality. Values approaching +1 for the silhouette score imply better clustering, whereas values closer to -1 indicate potential issues with clustering. Fig.4.5 shows that the DBSCAN clustering method outperforms the other two clustering methods.

4.3. Detectable Learning Index (DLI). When beta wave generation is higher for a given amount of time, learners are practically adapted to raise their degree of concentration. Our study highlights that technical undergraduate students will become more proficient learners if they can identify their learning preferences. During our experiment, the outcomes obtained regarding the participants' learning styles are shown in Table

Table 4.5: VARK Cognition Values of Participants

Sr. No.	V	A	RW	K	Max	Min	DLI	P	Va
1	78.59	52.67	70.48	64	78.59	52.67	Video	Video	T
2	61.64	57.73	58.46	58.78	61.64	57.73	Video	Video	T
3	63.91	44.36	68.57	66.18	68.57	44.36	RW	RW	T
4	10.82	35.13	13.06	52.79	52.79	10.82	Kine	Kine	T
5	22.07	31.84	63.33	54.8	63.33	22.07	RW	RW	T
6	81.45	85.1	55.46	32.19	85.1	32.19	Aural	Aural	T
7	67.58	78.21	58.68	52.78	78.21	52.78	Aural	Aural	T
8	33.42	74.83	70.6	58.25	74.83	33.42	Aural	Kine	F
9	33.26	74.83	58.68	52.78	74.83	33.26	RW	RW	T
10	43.43	45.32	31.15	40.7	45.32	31.15	Aural	Kine	F

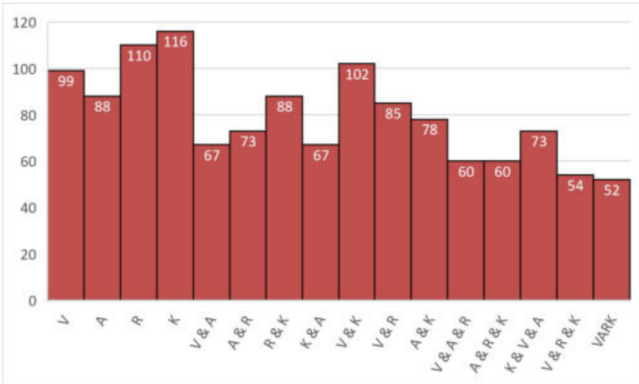


Fig. 4.6: Detectable Learning Index (DLI) for Four Sessions

4.5 for 10 students. Each row represents the values obtained for a particular participant.

For 10 participants, Table 4.5 includes columns for cognition values for V, A, R/W, and K learning styles, Maximum (Max) and Minimum (Min) of the cognition values, the DLI (Detectable Learning Index), actual learning preference of the participant (P) and the result of the validation (Va). The eSense algorithm of NeuroSky was used to obtain the cognition values for V, A, R/W, and K learning styles. The level of mental ”focus” or ”attention” is indicated by this algorithm. It represents a range of cognitive operations in the form of values. These values range from 0-100 and are sampled at the rate of 1 Hz for 2 minutes. When participants concentrate on the given content, their attention level rises; when they become distracted, it falls. The average of the attention level values are presented in Table 4.5 when the participants were given different types of learning materials.

The DLI represents the learning style computed by our proposed framework. For a total of 280 participants (N=280), four learning styles, Visual (V), Auditory (A), Reader/Writer (R/W), and Kinesthetic (K) are considered for generating the DLI. As discussed in the previous section, different clustering methods were used to identify the learning style, and based on this, the DLI was obtained. To validate the obtained DLI values, the actual learning styles of the participants were used as they provided them. The DLI values were compared with the actual learning styles of the participating students. If these two matched, the result of the validation, as depicted in the last column of Table 4.5, Va (Validation), was marked T (True), otherwise F (False).

In our experimental setup, the sample size N is 280, for which the statistical analysis has described a confidence level of (95%) with a margin of error of (5%). Out of 280 participants, 180 students (64.19%) were validated through a single learning modal, and 243 students accommodated the multi-modal learning style, resulting in 87% of students. The statistics show that of the learners with a single preferred skill (n=187,

Table 4.6: Detectable Learning Index (DLI)

Single Modal 64.19%	**Bi-modal 46%**	**Tri-modal 30.9%**	**Multi-modal 24.8%**
V-67%	VA-34%	VAK-3.8%	VARK-24.8%
A-45%	AR-32%	KVA-50.6%	
R-66%	VR-54%	ARK-28.3%	
K-77%	AK-52%	VRK-24.45%	
	VK-56	VAR-28.3%	
	RK-60%		

Table 4.7: Pearson Correlation Analysis

Parameter	**Pearson Correlation Co-efficient**	**Mean**	**Standard Deviation**
Gender	0.01	0.70	0.46
Stream	0.0123	0.02	0.27
Region	0.014	1.47	0.63
Age	0.065	19.21	1.09

67%) were engrossed in visual style, 126 learners (45%) had high Beta wave spikes while listening to the given content. 183 out of 280 learners (65.24%) have shown a high focus level while reading and writing to a given program, 193 learners, constituting 69.24% out of the complete sample size, have shown a high concentration level while subjected to debugging a program as presented in Table 4.6. This table shows the percentage of participants identified with specific learning styles based on their DLI that can be categorized as single-modal (a single learning style), bi-modal (a combination of any two learning styles), tri-modal (a combination of any three learning styles), and multi-modal (a combination of more than three learning styles).

4.4. Correlation between Learning Style and Demographic Parameters. In our study, the students who volunteered were 18 to 25 years old. The total count of participants was 280, out of which 168 students were male and 112 were female. We selected participants from the three regions of the Gujarat state: North Gujarat, South Gujarat, and Middle Gujarat. To assess whether any correlation exists between students' learning styles and parameters like Gender, Age, and Region, we applied a popular correlation method, Pearson Correlation [24]. The mean, standard deviation (SD), and Pearson Correlation Coefficient values computed for these parameters for all 280 participants are shown in Table 4.7.

The degree of the linear relationship between the two variables was determined by the Pearson correlation. It ranges from -1 to 1, where a value of -1 indicates a total negative linear correlation, a value of 0 indicates no correlation and a value of +1 indicates a total positive correlation. The Pearson correlation coefficient determines the degree of the linear relationship between two variables. A two-tailed test determines if a sample is more or less than a range of values by using a critical area with two sides of a distribution. The Sig(2-tailed) p-value was used to determine if the correlation was significant. Table 4.7 depicts the correlation obtained between different parameters associated with the learners.

As indicated in Table 4.8, the Pearson Correlation coefficient was computed to determine the independence of age with respect to the attention level. The results of the two-tailed test showed a value of -0.149, which is significantly lower than 0.5 and indicates no association between age and the observed attention levels for Beta waves and the learning styles. If each learner is given a unique learning environment, they all possess the same capacity for learning.

Table 4.8: Correlation between Student Age and Learning Style

		Age	Learning Style
Age	*Pearson Correlation*	1	-0.149**
	Sig. (2-tailed)		0.013
	N	280	280
Learning Style	*Pearson Correlation*	-0.149**	1
	Sig. (2-tailed)	0.013	
	N	280	280

4.5. Discussions. Our work indicates that undergraduates studying computer learning are simply accustomed to diving right into the practicals before fully grasping the concepts. Thus, the four learning styles — V, A, R, and K — are considered in this work. To prepare the teaching material or course content based on students' preferred learning styles, the following recommendations can be useful:

- V - Visual capability of the learners to understand through pictures, charts, differences in images, movies, figures and codes, and flowcharts.
- A - Aural/Auditory capability to understand from Audio clips, Podcasts, Group Study, and Audio Books.
- R/W - Reading/Writing capability of learners to comprehend manuscripts, programs, algorithms, textual descriptions, subject reference books, etc.
- K - Kinesthetic learners have the ability to solve problems through coding, debugging, and practical implementation. Such techniques should combine visual and/or auditory learning styles to emphasize multi-sensor learning.

5. Limitations and Future Scope. The proposed framework has a few limitations. The sample size of 280 learners may not be adequate to forecast the overall learning style of all the students enrolled in a particular course. Future research may include more learners to assign to the appropriate learning styles. Furthermore, the impact of various parameters associated with learners, such as prior domain knowledge, students' social and economic status, and other distinctive features, should be considered for improved accuracy. Additionally, in this work, the learning styles are derived only from EEG signals. Integrating additional learning assessment characteristics, such as body language, sign language, and facial expressions, can enhance the effectiveness of the teaching-learning process in real-world educational setups. Also, longitudinal data can provide insights into the sustainability and persistence of the observed enhancements in student learning.

6. Conclusions. This paper investigates the relationships between students' brain waves and their respective learning styles. Our proposed framework categorizes students based on their VARK learning styles. The participants are given different types of learning material for two minutes to understand their inclination towards specific learning modes and styles. Participants' beta brain waves are captured while they go through the visual, auditory, reading/writing, or kinesthetic content, and a database for the same is generated every second. Machine learning clustering algorithms such as K-means, DBSCAN, and Hierarchical are used to validate this dataset. This proposed approach proves to be a significant addition to the conventional teaching-learning paradigm for improved level of learning. Our research also established that various parameters associated with students, such as age, gender, region, etc., do not significantly correlate with their learning style preferences.

Due to the dissimilarities of the learner's understanding approach in the technical domain, it is recommended that the design of the course content, study material, and teaching methodologies be in a direction that befits the requirements of learners. Academic productivity will increase as a result, and the course outcomes will get better. Furthermore, considering that the practical training is hands-on, it is suggested that the related activities be included in the course curriculum. The study finds that if a learner's preferred learning style is determined, it will help them absorb information and turn it into knowledge. The student will be able to concentrate as the knowledge is added, and the activity will start to seem like fun rather than a tedious chore. The neurofeedback will train the mind to become more perceptive and capable of handling expected and unexpected malfunctions.

Learners can increase their efficiency by developing their natural cognitive ability. If the detectable learning styles follow instructional references with interactive problem-solving techniques, animations for kinematic learners, a graphical representation for visual learners, distinct color coding for reading/writing learners, and a storytelling approach for aural learners, an urge to learn can be enhanced. Machine Learning (ML) algorithms can be used to implement the analysis regarding the future scope of the study.

Data Availability Statement. The data supporting this study's findings are available on request from the corresponding author. The data are not publicly available due to information that could compromise the privacy of research participants.

REFERENCES

[1] R. Abiri, S. Borhani, E. W. Sellers, Y. Jiang, and X. Zhao, *A comprehensive review of eeg-based brain–computer interface paradigms*, Journal of neural engineering, 16 (2019), p. 011001.
[2] J. ALFORD, *Development of a spatial memory task in realistic virtual environments*.
[3] S. Amaniyan, V. Pouyesh, Y. Bashiri, S. Snelgrove, and M. Vaismoradi, *Comparison of the conceptual map and traditional lecture methods on students' learning based on the vark learning style model: A randomized controlled trial*, SAGE open nursing, 6 (2020), p. 2377960820940550.
[4] K. Amrulloh, T. Pudjiantoro, P. Sabrina, and A. Hadiana, *Comparison between davies-bouldin index and silhouette coefficient evaluation methods in retail store sales transaction data clusterization using k-medoids algorithm*, in 3rd South American International Conference on Industrial Engineering and Operations Management, 2022.
[5] P. Dreyer, A. Roc, L. Pillette, S. Rimbert, and F. Lotte, *A large eeg database with users' profile information for motor imagery brain-computer interface research*, Scientific Data, 10 (2023), p. 580.
[6] M. Forehand, *Bloom's taxonomy*, Emerging perspectives on learning, teaching, and technology, 41 (2010), pp. 47–56.
[7] D. J. Hagler Jr, S. Hatton, M. D. Cornejo, C. Makowski, D. A. Fair, A. S. Dick, M. T. Sutherland, B. Casey, D. M. Barch, M. P. Harms, et al., *Image processing and analysis methods for the adolescent brain cognitive development study*, Neuroimage, 202 (2019), p. 116091.
[8] M. Hasibuan, R. A. Aziz, and S. A, *Utilizing clustering algorithms to provide vark learning style recommendations*, in 2023 10th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), Sep. 2023, pp. 361–365.
[9] M. S. Hasibuan, L. E. Nugroho, and P. I. Santosa, *Model e-learning mdp for learning style detection using prior knowledge*, Int. J. Eng. Technol, 7 (2018), pp. 118–122.
[10] C. Jeunet, B. N'Kaoua, S. Subramanian, M. Hachet, and F. Lotte, *Correction: Predicting mental imagery-based bci performance from personality, cognitive profile and neurophysiological patterns*, Plos one, 18 (2023), p. e0282281.
[11] K. Khan, S. U. Rehman, K. Aziz, S. Fong, and S. Sarasvady, *Dbscan: Past, present and future*, in The fifth international conference on the applications of digital information and web technologies (ICADIWT 2014), IEEE, 2014, pp. 232–238.
[12] D.-H. Kim, D.-H. Shin, and T.-E. Kam, *Bridging the bci illiteracy gap: a subject-to-subject semantic style transfer for eeg-based motor imagery classification*, Frontiers in Human Neuroscience, 17 (2023), p. 1194751.
[13] T. M. Kodinariya, P. R. Makwana, et al., *Review on determining number of cluster in k-means clustering*, International Journal, 1 (2013), pp. 90–95.
[14] S. Koenig, G. P. Crucian, A. Dünser, C. Bartneck, and J. C. Dalrymple-Alford, *Validity evaluation of a spatial memory task in virtual environments*, Int J Des Innov Res, 6 (2011), pp. 1–13.
[15] L. Kovtun, N. Zenenko, and E. Lapteva, *Effects of students learning styles on adaptive e-learning design*, in 2021 IEEE International Conference on Educational Technology (ICET), June 2021, pp. 184–190.
[16] T. Kustermann, N. A. N. Nguissi, C. Pfeiffer, M. Haenggi, R. Kurmann, F. Zubler, M. Oddo, A. O. Rossetti, and M. De Lucia, *Electroencephalography-based power spectra allow coma outcome prediction within 24 h of cardiac arrest*, Resuscitation, 142 (2019), pp. 162–167.
[17] A. M. Medina, F. J. C. García, and J. A. M. Olguín, *Planning and allocation of digital learning objects with augmented reality to higher education students according to the vark model*, IJIMAI, 5 (2018), pp. 53–57.
[18] M. A. Mirza and K. Khurshid, *Impact of vark learning model at tertiary level education*, International Journal of Educational and Pedagogical Sciences, 14 (2020), pp. 354–361.
[19] V. Movchun, R. Lushkov, and N. Pronkin, *Prediction of individual learning style in e-learning systems: opportunities and limitations in dental education*, Education and Information Technologies, 26 (2021), pp. 2523–2537.
[20] R. Nazempour and H. Darabi, *Personalized learning in virtual learning environments using students' behavior analysis*, Education Sciences, 13 (2023).
[21] F. Nielsen and F. Nielsen, *Hierarchical clustering*, Introduction to HPC with MPI for Data Science, (2016), pp. 195–211.
[22] K. Nordhausen and H. Oja, *Independent component analysis: A statistical perspective*, Wiley Interdisciplinary Reviews: Computational Statistics, 10 (2018), p. e1440.
[23] B. Ntwali, *Investigating the relationship between learning styles and delivery methods in information security awareness programs*, master's thesis, Faculty of Commerce, 2021.

[24] E. I. Obilor and E. C. Amadi, *Test for significance of pearson's correlation coefficient*, International Journal of Innovative Mathematics, Statistics & Energy Policies, 6 (2018), pp. 11–23.
[25] R. Rajkumar and V. Ganapathy, *Bio-inspiring learning style chatbot inventory using brain computing interface to increase the efficiency of e-learning*, IEEE Access, 8 (2020), pp. 67377–67395.
[26] R. Rajkumar and V. Ganapathy, *Bio-inspiring learning style chatbot inventory using brain computing interface to increase the efficiency of e-learning*, IEEE Access, 8 (2020), pp. 67377–67395.
[27] N. Rane, S. Choudhary, and J. Rane, *Education 4.0 and 5.0: Integrating artificial intelligence (ai) for personalized and adaptive learning*, Available at SSRN 4638365, (2023).
[28] A. Rezeika, M. Benda, P. Stawicki, F. Gembler, A. Saboor, and I. Volosyak, *Brain–computer interface spellers: A review*, Brain sciences, 8 (2018), p. 57.
[29] T. Ros, S. Enriquez-Geppert, V. Zotev, K. D. Young, G. Wood, S. Whitfield-Gabrieli, F. Wan, P. Vuilleumier, F. Vialatte, D. Van De Ville, et al., *Consensus on the reporting and experimental design of clinical and cognitive-behavioural neurofeedback studies (cred-nf checklist)*, 2020.
[30] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H. Falk, and J. Faubert, *Deep learning-based electroencephalography analysis: a systematic review*, Journal of neural engineering, 16 (2019), p. 051001.
[31] S. Sageengrana, S. Selvakumar, and S. Srinivasan, *Optimized rb-rnn: Development of hybrid deep learning for analyzing student's behaviours in online-learning using brain waves and chatbots*, Expert Systems with Applications, (2024), p. 123267.
[32] S. Sageengrana, S. Selvakumar, and S. Srinivasan, *Optimized rb-rnn: Development of hybrid deep learning for analyzing student's behaviours in online-learning using brain waves and chatbots*, Expert Systems with Applications, 248 (2024), p. 123267.
[33] M. A. M. Sahagun, *Prediction of electronics engineering student's learning style using machine learning*, in 2021 1st Conference on Online Teaching for Mobile Education (OT4ME), Nov 2021, pp. 42–49.
[34] S. Sakhavi, C. Guan, and S. Yan, *Learning temporal information for brain-computer interface using convolutional neural networks*, IEEE transactions on neural networks and learning systems, 29 (2018), pp. 5619–5629.
[35] K. K. Srinivas, A. Peddi, B. G. S. Srinivas, P. A. H. Vardhini, H. L. P. Prasad, and S. K. Choudhary, *Artificial intelligence techniques for chatbot applications*, in 2022 International Mobile and Embedded Technology Conference (MECON), March 2022, pp. 292–296.
[36] J. Stander, K. Grimmer, and Y. Brink, *Learning styles of physiotherapists: a systematic scoping review*, BMC medical education, 19 (2019), pp. 1–9.
[37] A. Vallabhaneni, T. Wang, and B. He, *Brain—computer interface*, in Neural engineering, Springer, 2005, pp. 85–121.
[38] S. Vanbecelaere, K. Van den Berghe, F. Cornillie, D. Sasanguie, B. Reynvoet, and F. Depaepe, *The effects of two digital educational games on cognitive and non-cognitive math and reading outcomes*, Computers & Education, 143 (2020), p. 103680.
[39] T. M. Vaughan, W. J. Heetderks, L. J. Trejo, W. Z. Rymer, M. Weinrich, M. M. Moore, A. Kübler, B. H. Dobkin, N. Birbaumer, E. Donchin, et al., *Brain-computer interface technology: a review of the second international meeting.*, IEEE transactions on neural systems and rehabilitation engineering: a publication of the IEEE Engineering in Medicine and Biology Society, 11 (2003), pp. 94–109.
[40] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, T. M. Vaughan, et al., *Brain-computer interface technology: a review of the first international meeting*, IEEE transactions on rehabilitation engineering, 8 (2000), pp. 164–173.
[41] J. R. Wolpaw, D. J. McFarland, G. W. Neat, and C. A. Forneris, *An eeg-based brain-computer interface for cursor control*, Electroencephalography and clinical neurophysiology, 78 (1991), pp. 252–259.
[42] R. S. Wyer and T. K. Srull, *Human cognition in its social context.*, Psychological Review, 93 (1986), pp. 322–359.
[43] B. Zhang, C. Chai, Z. Yin, and Y. Shi, *Design and implementation of an eeg-based learning-style recognition mechanism*, Brain Sciences, 11 (2021).
[44] B. Zhang, Y. Shi, L. Hou, Z. Yin, and C. Chai, *Tsmg: A deep learning framework for recognizing human learning style using eeg signals*, Brain Sciences, 11 (2021).
[45] S. Zhao, W. Guan, G. Qi, and P. Li, *Heterogeneous overtaking and learning styles with varied eeg patterns in a reinforced driving task*, Accident Analysis & Prevention, 171 (2022), p. 106665.
[46] R. A. Zwaan, D. Pecher, G. Paolacci, S. Bouwmeester, P. Verkoeijen, K. Dijkstra, and R. Zeelenberg, *Participant nonnaiveté and the reproducibility of cognitive psychology*, Psychonomic bulletin & review, 25 (2018), pp. 1968–1972.

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