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Bio-Inspiring Learning Style Chatbot Inventory Using Brain Computing Interface to Increase the Efficiency of E-Learning

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ABSTRACT In recent times Electronic Learning (E-Learning) and Massive Open Online Courses (MOOC) are more popular among the current generation of learners. Coursera, Edx, Simplilearn, Byjus and many other E-Learning service providers are available to deliver various courses. A recent study, in online courses, it has been found by Massachusetts Institute of Technology (MIT) that an astronomical dropout rate of about 96 per cent was found for the last five years. Educational researchers are attempting to decrease the dropout rate of E-Learning courses using various methods. Human Computer Interface (HCI) researchers are attempting to use Brain Computer Interface (BCI) to increase the efficiency of the E-Learning. Beta waves (14-30 Hz) are generated when the learners are more alert. Neil Fleming's VARK (Visual, Auditory, Read and Write and Kinesthetic) questionnaires are used by many researchers to classify the learners. Carl Jung explored that Introverts and Extraverts are the personality traits among the humans. Soomin Kim's study shows that for gathering of quantitative data, Chatbot may be a promising method. The proposed research work in this paper is to find out a correlation between Introvert and Extravert personality types and their learning styles. Initially, modified VARK questionnaires are implemented as a Chatbot to classify individuals as Introverts or Extraverts. After the classifications by the Chatbot, two minutes of visual and auditory contents are given to Introverts and Extraverts and learners' Beta brain waves are recorded and a dataset is created at an interval of one second. The dataset is validated using Machine Learning (ML) algorithms, like Naïve Bayes, N48 and Canopy. The proposed method is found to improve the accuracy of classification of learners. Bio-Inspired learning style Brain Computing Interface (BIL-BCI) framework proposed in this paper is a recommendation system to increase the accuracy of the classification among the E-Learners.

INDEX TERMS E-Learning, massive open online course, VARK learning style, learning styles inventory(LSI), chatbot, classification, machine learning, introverts, extraverts, brain computer interface.

I. INTRODUCTION

Internet is expanding to a larger extent to reach all over the world. The average global internet speed is getting faster. Educational technologies [1] have become more viable with the advent of Internet. The higher education process has been dramatically changed by the use of latest techniques and tools. Modern technologies are increasing to have easy access for learning. Human's learning online can be changed by the E-Learning and MOOCs process. A large number of learners can learn online at their own pace by using MOOC. Open course materials and peer feedbacks are used by the learners to interact with the courses. Around the globe, many universities are offering learners a chance to learn their relevant courses through MOOCs.

E-Learning [2] has a unique preference for learning and learning goals. Individual needs can be accommodated in E-Learning courses. E-Learning allows the learners to select their own learning paths and navigate at their own speed. If learners are able to decide as what to learn and when to learn on their own they continue to study the courses.

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E-Learning has many advantages as compared to the traditional learning systems. A recent study, in online courses, it has been found by Massachusetts Institute of Technology (MIT) that an astronomical dropout rate of about 96 per cent has been recorded for the last five years. Few MOOC courses are having less than 30 percentages of completion rates [3]. Many millions of learners, who have participated in MOOCs, the vast majority do not get to the stage of obtaining their completion certificates.

According to the study by Rivard [4], the following reasons are arrived at for incompletion of the registered MOOC courses by E-learners.

1. No real intention to complete
2. Low motivation
3. Lack of attention
4. Lack of time
5. Course difficulty
6. Expectations and
7. Starting late.

In recent times, it is found that different people learn in different ways. To improve the learning process and to help people to become efficient learners, a personalized approach is needed [5]. In common, there are two types of learning environments; they are Individual Learning environments and Group Learning environments. The Individual learners learn more effectively on their own without the support of others. Group learners learn more effectively when they are in groups. For Individual and Group learners, separate course contents should be prepared to meet their respective learning needs.

In 1970's, individual learning became popular [6]. Despite criticism from various researchers regarding individual learning, E-Learning had greatly influenced education. In recent years, learning styles have gained so much attention across different age groups and learning environments. Many of the researchers are considering for preparation of the course contents using learning styles.

Human learners differ in the way they learn. A range of competing contests which are accounted for differences in individual learning styles [7]. Many theories have been proposed in which humans can be classified based on their style of learning. Different psychological characteristics are indications of how the interaction takes place amongst the individuals and their responses to the learning environment.

Scientists [8] who have done extensive research have criticized the various learning style approaches. Lack of measurement of learning style is the major critique to the learning style Inventory (LSI). Some unavoidable limitations are there in the web services. One of the limitations is that less reliable responses are produced as compared to face to face or telephonic surveys where their responses give insincere answers.

The learning experiences are becoming smarter with the advent of new technologies. A new learning culture has been introduced in Artificial Intelligence powered Chatbot. In order to engage the users, it is necessary to make the experience personalized. This helps the e-Learning providers and educators to meet the goals of intended education. Chatbot takes the personalization level to a new height. Creation of Chatbot is an ideal way to take learning to a personal level instead of questionnaires.

Winnie Frances Leung [9] proposed Introversion and Extraversion personality traits.

Extravert traits prefer to exchange ideas. They are comfortable with working in teams, group projects, and learning mimicking experiences.

The following are the important qualities of Extravert traits:

- They are outgoing in nature
- They are comfortable in working with large crowds
- They prefer to know a lot of people and move with more number of friends.
- If they spend too much time alone, they become week.
- They have social learning style.

In addition, extraverts have strong verbal learning styles as well, and they often communicate through stories. Usually, they are the first people to volunteer for assignments and projects. They are good in managing team.

Introverts are shy in nature. They have unique learning style, as they want to solve problems on their own. They are interested to seek theoretical explorations before moving forward to think out a problem.

The following are the important qualities of Introverted traits: They

- seem to be reserved or reflective.
- think much before taking actions.
- may have a very small group of friends.
- want to know a few people really well.
- feel good when they are alone.
- prefer to do things which can be done alone

In brain, the dopamine [10] functions as a neurotransmitter which is a chemical released by neurons (nerve cells) to send signals to other nerve cells.

Introvert and Extraverts personality traits respond in different ways to the neurotransmitter dopamine. Comparing to the Introvert, Extraverts are more activated with more dopamine being in a crowd. So, they become more talkative in crowded places. It is not that Introverts have less dopamine present in their brain; actually, Introverts and Extraverts both have the same amount of dopamine in their brains, but the activities of the dopamine are different with each other due to reward network. The dopamine of brains of Introverts is more active than in the brains of Introverts when they are alone.

Learners may be classified into Introverts or Extraverts. The proposed work is to attempt the classification of Introvert and Extraverts for learning style Inventory (LSI). Initially, modified VARK questionnaires are implemented as a Chatbot to interact with learners. After the classification from the Chatbot, two minutes of visual and auditory contents are given to the learners to watch in a silent atmosphere. While watching the contents, learners' Beta brain waves are recorded and a dataset at the interval of every one second is created for further processing.

The dataset is trained using machine learning algorithms like Naïve Bayes and J48 tree classification algorithms available Weka 3.8.3 data mining tool. In this research, the accuracy of the proposed method is compared with the accuracy of the Fleming's VARK online questioner method regarding the classification of learners. The learners with different age groups and with both genders are chosen for the proposed experimentations. The Chatbot and two minutes of visual and auditory contents are tested with 118 learners from SRM Institutes of Science and Technology, Kattankulathur, India. The learners cover over a wide range of age and gender. A sample E-Learning content is tested and common assessment results have been recorded.

II. LITERATURE REVIEW

A. E-LEARNING

Unlimited participation and open access via web are the features of an E-Learning. In addition to traditional course materials in E-Learning readings, video lectures and text are enriched. In E-Learning, interactive courses have emerged to support the community interactions between learners and teachers. This will enable the learners to provide immediate feedback to quick quizzes and assignments. The addition of learning styles in E-Learning enables to customize E-Learning platforms. The recent researches are emerging to find out the classification of the learners in E-Learning to reduce the dropout rates ofE-Learners.

B. LEARNINGSTYLES

Individual differences in E-Learning are some of the considerable features of E-learning. Cognitive processes, emotions, environment, family and culture of an individual affect the learning, which are considered to be a complex process. The differences within individuals learning processes are highlighted in (Erden and Altun, 2006). How skills and contents can influence individuals learning is discussed in (Johassen and Grabowski, 1993).

Dunn and Dunn learning style Model [11] has been proposed to empower and educate teachers and parents to analyze and motivate learners and to optimize their education to their unique learning preferences. It is observed that the creators recognized that most learners learn differently and many of the learners need to be taught differently. Dunn and Dunn learning style model contains five elements which are Sociological, Emotional, Environmental, Physiological and Psychological. This model lays out a comprehensive set of elements that can influence a learner instead of prescribing a fixed style for each learner.

For improving performances especially in higher education Kolb's learning style Model [12] is widely accepted. Kolb postulated the theory that different learning styles are preferred by different people. The combination of two separate learning styles decides the learning style preference itself.

Based on the work of Kolb, learning style model [13] was developed by Peter Honey and Alan Mumford. Four distinct learning styles Activist, Theorist, Pragmatist and Reflector are identified by them. The above four learning styles are preferred and they recommend to maximize one's own personal learning. It has advantages that the attitudes and behaviors can be used to determine the preferences with regards to learning.

Felder and Silverman learning style model [14] consists of four dimensions, and each dimension expresses a different aspect of learning with a linguistic variable. These dimensions can be explained with respect to the way the learners perceive information. They may be modelled as ''intuitive'' or ''sensing'' learners. Also, the learners can be modelled as ''verbal'' or ''visual'' based on the way the learners receive information. Learners can also be distinguished as ''active'' or ''reflective'' related to the way they process information. And again, learners can be modelled as ''sequential'' or ''global'' depending on whether they learn in sequence one by one or at a stretch. Fleming proposed VARK (VARK-Visual, Auditory, Read / Write, Kinesthetic model) learning style Model [15].

C. BIG FIVE PERSONALITY TRAITS

Many researchers believe that they are five core personality traits [70]. Big five are broad categories of personality traits. Openness, conscientiousness, extraversion, agreeableness, and neuroticism are the big five personality traits. The Big five theory emerged to describe the essential traits that serve as the building blocks of personality. Research study [71] shows that personality traits are influencing in their learning styles.

1) OPENNESS

Openness is a general appreciation for unusual ideas, adventure, curiosity, imagination art, emotion and variety of experience. People who are open to experience, they are intellectually curious, open to emotion and willing to try new things. They are also more likely to keep unconventional beliefs. High openness can be perceived as unpredictability that makes lack of focus, and more likely to engage in risky behavior. Moreover, people with high openness are said to pursue self-actualization specifically by seeking out intense.

2) CONSCIENTIOUSNESS

Conscientiousness is a tendency to display self-discipline, act dutifully, and strive for achievement against measures or outside expectations. It is related to the way in which people control, regulate, and direct their impulses. High conscientiousness is often perceived as being stubborn and focused. Low conscientiousness is associated with flexibility and spontaneity, but can also appear as sloppiness and lack of reliability. High scores on conscientiousness indicate a preference for planned rather than spontaneous behavior. The average level of conscientiousness rises among young adults and then declines among older adults.

3) EXTRAVERSION

Extraversion is characterized by breadth of activities (as opposed to depth), urgency from external activity/situations, and energy creation from external means. The trait is marked by pronounced engagement with the external world. Extraverts enjoy interacting with people, and are often perceived as full of energy. They tend to be enthusiastic, action-oriented individuals. They possess high group visibility, like to talk, and assert themselves. Extraverted people may appear more dominant in social settings, as opposed to introverted people in this setting. Introverts have lower social engagement and energy levels than extraverts. They tend to seem quiet, low-key, deliberate, and less involved in the social world. Their lack of social involvement should not be interpreted as shyness or depression; Introverts need less stimulation, and more time alone than extraverts. This does not mean that they are unfriendly or antisocial; rather, they are reserved in social situations.

Generally, people are a combination of extraversion and introversion, with personality psychologist Eysenck suggesting that these traits are connected somehow to our central nervous system.

4) AGREEABLENESS

The agreeableness trait reflects individual differences in general concern for social harmony. Agreeable individual's value getting along with others. They are generally considerate, kind, generous, trusting and trustworthy, helpful, and willing to compromise their interests with others. Agreeable people also have an optimistic view of human nature. Disagreeable individuals place self-interest above getting along with others. They are generally unconcerned with others well-being, and are less likely to extend themselves for other people. Sometimes their skepticism about others motives causes them to be suspicious, unfriendly, and uncooperative. Low agreeableness personalities are often competitive or challenging people, which can be seen as argumentative or untrustworthy.

5) NEUROTICISM

Neuroticism is the tendency to experience negative emotions, such as anger, anxiety, or depression. It is sometimes called emotional instability, or is reversed and referred to as emotional stability. According to Eysenck's (1967) theory of personality, neuroticism is interlinked with low tolerance for stress or aversive stimuli. Neuroticism is a classic temperament trait that has been studied in temperament research for decades, before it was adapted by the Five Factor Model (FFM). They are more likely to interpret ordinary situations as threatening, and minor frustrations as hopelessly difficult. At the other end of the scale, individuals who score low in neuroticism are less easily upset and are less emotionally reactive. They tend to be calm, emotionally stable, and free from persistent negative feelings. Freedom from negative feelings does not mean that low-scorers experience a lot of positive feelings.

D. RELATON BETWEEN BLOOD TYPE AND HUMAN CHARECTRISTICS

Hobgood [24] proposed that ABO blood groups influence in personality traits. There are several evidences that A, B, AB and O blood types are associated with various diseases including cardiovascular, cancer, and stress responses [25]. There are reports that specific learning styles are inherited with Introvert and Extravert personality types [26]. Psychology researchers [27], [28] established that ABO blood types are also associated with Introvert and Extravert types among the learners

Extraverts and Introverts are associated with their respective blood types. Japanese Professor Tokeji Furukawa [29] published a paper claiming that each blood type reflects the personality of a person. The four primary blood types, A, O, B and AB are differentiated from each other based on the irantigens.

In general, people differ in their blood types [30]. 'A' blood type people are cooperative, emotional, passionate, sensitive and clever. They are very patient and loyal. But these people become overly sensitive sometimes. These people take their time to make decisions and are too organized in all spheres of life. They like things to be neat, clean and put at the right place.

People with blood type 'A' are get stressed easily and thus have a high level of cortisol hormone. These people are very creative and quick decision makers. But they are not good at taking orders. They put every part of themselves into something they want to focus on. They have a very strong desire and drive to be the best of everything they do. These people are not good at multi-tasking.

Creativity and quick decision making are the qualities of 'B' blood type People. But they are also not good at taking orders. They put every part of themselves into something they want to focus on. They have a very strong desire and drive to be the best of everything they do. But just like the 'A' blood type, these people are also not good at multi- tasking. People with 'B' blood type are thoughtful and empathetic towards others and make good and reliable friends.

Blood type 'AB' has the mix of People 'A' and people 'B' qualities. These people are the rarest blood type in the world. Hence, dual personalities exist in them. AB blood type can be shy, like 'A' blood type, and outgoing like 'B' blood type. They do not reveal their personalities to strangers which make others to believe that they belong to a mixed personality. They make friendship easily and look charming always. In a group of friends they will never be in a dull moment even if only one of them is 'AB' blood type. They are poor at handling stress. 'AB' blood type people are very careful while dealing with others and are empathetic. Exceptional analytical and logical skills are possessed by these people.

Daring, outgoing and go-getters are the qualities of the people with blood type 'O'. They have a habit of setting high standards for themselves and they go to any extend to achieve them. Little things do not bother them and they have excellent leadership qualities. They are kind-hearted and generous, loving and resilient. They are flexible at tough situations.

Sivaraman [31] proposed the association between the blood types with Introverts and Extravert personality types. Blood types of 500 people are identified in which 58 are of 'A', 79 numbers are of 'B', 96 numbers are of 'O' and 17 numbers are of 'AB' blood types and these 500 people are classified into Introvert and Extravert. In Table 1, Sivaraman's works on basic blood types and their chances of Introvert and Extravert are given.

TABLE 1. Blood type and chances of introvert and extravert types [31].

S.	Blood type	Chance of Introvert	Chance of Extravert
1	Type A	High	Low
2	Type B	Low	High
3	Type O	High	High
4	Type AB	High	Low

E. HUMAN BRAIN WAVES

MIT's Earl K. Miller [32], a Professor of Neuroscience says that, the distinct neural signatures should guide researchers as they study the underlying neurobiology of how humans both learn motor skills and work through tough cognitive tasks. The researchers Freedman [33], Nieder [34] and Pasupathy [35] found that different types of behaviours are accompanied by different patterns of brain waves. Figure 1 shows different brain waves produced for a healthy adult.

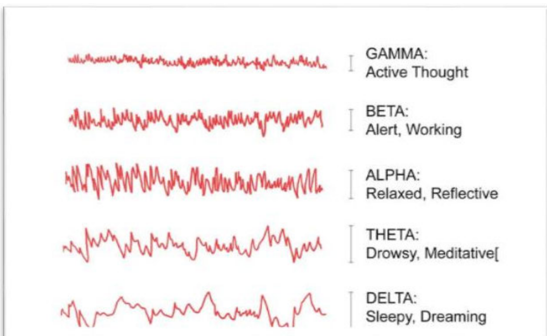


FIGURE 1. Healthy adult brain waves [42].

Learning engages all the senses and taps the emotional side of the brain through methods like storytelling, humor, group activities and games. Human brain contains more than 100 billion nerve cells called neurons and each neuron individually is linked to other neurons through axons and dendrites. Basically, a small amount of electric signal in microamperes range moves from one neuron to other neuron [36] to carry out the numerous activities of the brain.

These signals produced by the brain can be divided into five frequencies like Gamma, Beta, Theta, Alpha and Delta as given in Table 2.

TABLE 2. Brain waves and their associated activities [37].

Brain waves	Frequency Range	Associated state of mind
Gamma	30 - 100 Hz	Anxiety, Depression, High Arousal, Stress
Beta	14-30 Hz	Alert, normal alert consciousness, Active conversation, Making decisions, Learning.
Alpha	8-13 Hz	Yoga, Just before falling asleep, Being creative and artistic.
Theta	4-7 Hz	Deep meditation, Daydreaming.
Delta	< 3.5 Hz	Sleep, Dreaming

Each brain wave is associated with a state of the mind and every frequency has two categories [37] like spikes and field potential. There are considerable insights [38] into how different types of learning styles are characterized by the brain. There are notable researches [39], [40], [41] that were published for BCI technology in E-Learning context. With reference to the Table 2, it is observed that the Beta waves are generated while learning and keeping high concentration. To identify the learning styles and learning preferences, learners' brain wave data can be of much use.

F. MACHINE LEARNING FOR PERSONALIZATION

Machine Learning is said to be learning from past experiences with respect to some class of tasks, and the learning improves with the experience [43]. Machine learning makes use of algorithms that are designed to improve over time depending on the new data they will be tracking. It enables systems to make decisions that are data-driven eliminating the need for explicit programming to execute a task and can be effectively utilized in E-Learning applications. One of the applications is personalized learning paths that can be changed dynamically based on the progress of the learner.

G. CHATBOT FOR LEARNINGPLATFORM

One of the most thriving E-Learning innovations is the Chatbot technology [45]. Chatbot works on the principle of interacting with users in a human-like manner. Artificial Intelligent and Content based Chatbot are becoming essential parts of E-Learning environment. Learners are exposed to Chatbot and other virtual assistants on their personalized devices. These intelligent bots are often deployed as virtual assistants. Chatbot provides conversational answers and serve as a quick reference guide. Chatbot potentially can tap into various sources of information to the knowledge management tool. It is used to pinpoint certain learning patterns, such as significant spikes in course dropouts. Increasingly, there are applications for coaching support and intelligent tutoring system.

H. MACHINE LEARNING APPLIED TO E-LEARNING

Studies [44] found that learners who are taught according to their identified learning styles do no better than learners who are not matched to their learning styles. In the past decades, many learning style models have been proposed, and some of these learning style models have been found more suitable for E-Learning. However, research on learning style inventories might be a way for learners to develop E-Leaning contents that keep them interested and engaged in the learning process and this may find useful for the learners to discover their learning preferences. For example Visual learners might be more interested with symbols, graphs, and other visual information while studying the E-Learning materials. Machine Learning (ML) provides many effective ways to analyze learner's engagement data and identify patterns that suggest which content could be better redesigned, or to provide more support to learners who are failing to complete a MOOC course. ML and BCI are the emerging technologies that can apply machine learning algorithms to classify learners and deliver the appropriate E-Learning contents to increase the engagement of E-Learning courses.

I. BRAIN COMPUTER INTERFACE FOR CLASSIFICATION USING MACHINE LEARNING

Seyed [50] has proposed that the brain anatomy of each individual is different in many aspects. There is a study conducted by Chris [51], [52] which shows that the Extravert and Introvert classification leads to identify the learning styles to which they belong to. Chris concludes that Introverts prefer to study alone. They like calm places to study and they hardly prefer group learning. Extraverts prefer to have combined study. They like music and audio books for learning. Swiss psychiatrist and psychotherapist Carl G. Jung [18] [70] categorized human beings as either Extraverts or Introverts. The author saw human behaviours and habits as patterns, and attempted to understand and explain differences in personalities according to those unique and variable patterns. As shown in Figure 2, Introverts are thoughtful, keep emotions private quiet and think before acting and like to spend more time alone. Extraverts are talkative, openly show their emotions, and act before thinking and like to be with people always. Introverts and Extraverts brains differ in many aspects.

However, with the development of neuro-imaging technologies quantitative evidences suggest that the brains of extraverts and introverts are different [19].

Introvert-Extravert spectrum by looking at neural differences in the regional cerebral blood flow is investigated by researchers Fischer, Wik, and Fredrikson [20]. One of the findings suggests a dopaminergic basis for individual differences in extraversion. The activity in the putamen of the brain was left-lateralized, with these areas having high concentrations of dopamine terminals for Introverts.

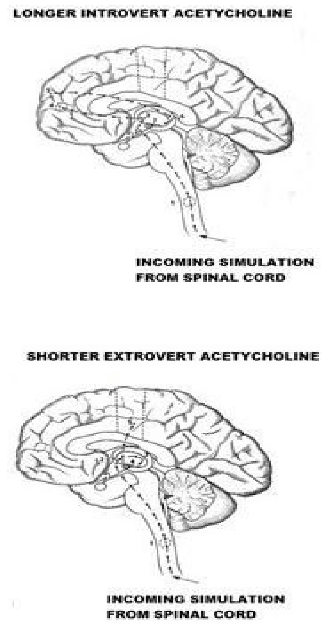


FIGURE 2. Difference between introvert and extravert in brain anatomy.

As shown in Figure 2, Extraversion is associated with activation in regions of the anterior cingulate cortex that is related to decision-making and socially-driven interactions. The dorsolateral prefrontal cortex which is having executive functions such as working memory and cognition, middle temporal gyrus for semantic memory and language and the amygdale, is for processing emotions. When stimulation enters an extravert's brain [21], the pathway to process it is much shorter. It travels through areas of the brain where touch, visual, taste and auditory sensory processing take place.

For Introverts, stimulation travels through a long and a complicated pathway through many areas of brain, including the right front Broca's area – self-talk, insular – empathy and Left hippocampus–personal. Introverts may process information more thoroughly and deeply than extraverts doing the thought processing. The research of Castro [22] has proved that there are scientific and general differences between Introverts and Extraverts.

According to the study, Extraversion is a phenomenon, in which the human brain needs constant stimulation and radiates energy in the form of intense emotions and feelings. Extraverts need a driving force to motivate them and they also like to have constant changes. Brain Computer Interface (BCI) is an advanced version of emerging technology called Human Computer Interface (HCI). Recently, non-invasive BCI sensor devices are commercially available for gaming and learning context. BCI products like Muse [53] and Neuorosky [54] are used in meditation and concentration training. These devices are absolutely wire free. They can connect with communication interface platforms like Infra-Red and Bluetooth technologies.

The hardware of the BCI devices is able to connect with the mobile devices like iPhone and Android phones. Neurosky Mind wave Mobile 2 [55] is a single electrode BCI device which is made use of in capturing the EEG signals for experiments in this study. The electrodes are placed as shown in Figure 3 on the skull.

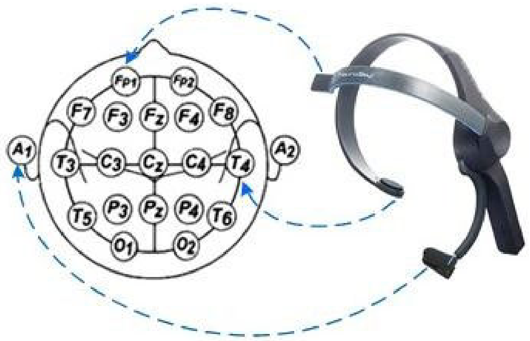


FIGURE 3. Neurosky BCI device and its electrode positions [55].

Based on the international "10-20 system" [56], data is captured for one second intervals. FP1 and T4 are the electrode positions in the head, and A1 is a reference electrode. Actually, brain signals are of very low amplitude energy signals. The BCI device amplifies these signals which become compatible to interface with the computer. The receiver side of the mobile device is a mobile application called EEG ID [57]. It is light weighted application and it can connect with Neurosky device through Bluetooth connection. EEG ID using the EEG signals can be recorded at intervals of minutes, seconds and milliseconds. The Learner can generate BCI waves and that will be converted into Comma Space Value (CSV) file through EEG ID Mobile application. Here the Beta signals [58] are considered to measure the real time learning efficiency of the learners. They are produced when the brain is more active and get invoked in learning.

III. PROPOSED METHOD

The proposed system has two experimentations. The first experimentation is to design a Chatbot for classification of learners. The proposed Chatbot is designed for the purpose of knowing the learners' likes and dislikes while learning. Learner's preferences like their habits, liking color and willingness in group study are tested. For example, the Extroverts prefer group learning and Introverts like blue color. Thus, the Learners can be classified into Introverts and Extroverts using Chatbot.

The second experimentation is to design a Brain Computer Interface system. The learning styles are examined by analyzing the Brain wave (EEG) signals, and the machine-learning classifier is used for the classification of learners into Visual learners and Auditory learners. Learners have undergone an experimentation to see a multimedia video for a particular time. The video contains stimuli contents of Visual and Auditory learning styles. While watching the video, learners' EEG signals are recorded and datasets are created.

Initially, modified VARK questionnaires are implemented as a Chatbot to classify the individuals as Introverts or Extraverts. The Chatbot is intended to know the learners' preferences manually. The conversation of the Bot [46] in Chatbot is likely to interact with the learners to know the basic information like age group, habits and learning preferences. The habit like taking tea or coffee makes sense at a study [47] conducted in 2017, explored the link between personality type and blood group. As per the study [48] it is concluded that there is a strong correlation between Introvert and Extravert type people with their learning styles. The Chatbot interacts with the learners to classify them into Introverts and Extraverts.

The proposed system is a content based approach in learning styles. Content based learning style is called VARK model and it is widely used for Adaptive E-Learning environment [16]. Because of its content based approach in learning, the VARK model remains fairly popular even though it has a lot of criticisms and lack of empirical support.

A. INSTRUMENTS-VARK QUESTIONNAIRES

The VARK questionnaires are given to the learners before they attempt to learn the courses [17]. A learner has to select the answer which best explains his/her preference and circles the letter next to it. If a single answer does not match the learners' perception, learners have to circle more than one choice. If questions are tough to answer, learner should leave the question unanswered, but the learner has to give answers for at least 10 out of the 13 questions.

Table 3 contains the VARK learning style and its prescribed learning contents.

TABLE 3. Prescribed learning contents for VARK learning style [17].

S. No	Learning styles	Prescribed Learning contents
1.	Visual Learners	Pictures, Text, Animation, Diagrams etc.
2.	Auditory Learners	Voice Narration, Audio books, Music, Video etc.
3.	Read / Write Learners	Self-study by text, Own notes etc.
4.	Kinesthetic Learners	Physical actions and sense of touch etc.

Table 4 contains the sample VARK Learning Style Inventory (LSI) chart. The VARK learning style is used in most of the recent E-Learning systems.

TABLE 4. Sample VARK learning style inventory chart [17].

Categories / Questions	A Category	B Category	C Category	D Category
1	K	A	R	V
2	V	A	R	K
3	K	V	R	A
4	K	A	V	R
5	A	V	K	R
6	K	R	V	A
7	K	A	V	A
8	R	K	A	V
9	R	A	K	V
10	K	V	R	A
11	V	R	A	K
12	A	R	V	K
13	K	A	R	V
14	K	R	A	V
15	K	A	R	V
16	V	A	R	K

By sorting the number of repeated choices V, A, R, and K, the value of learning style can be calculated. The highest value amongst V, A, R, and K categories would be the learning style of the learner.

The scores obtained are

V= 6; A= 2; R= 4; and K = 3;

If the scores V, A, R and K are arranged in a descending order, it becomes,

V > R > K > A

From the above, it is concluded that this Learner is classified as a Visual learner. Thus the Learning Style Inventory (LSI) can be identified using VARK learning style model.

According to the E-Learning, Read/Write Learning and Kinesthetic learning styles are not possible to implement. Chris [51], [52] concludes that Introverts prefer to study alone. They like calm places to study and they hardly prefer group learning. Extraverts prefer to have combined study. They like music and audio books for learning.

After the classification by the Chatbot as Introvert and Extravert, the learners are exposed to two minutes of visual and auditory contents to watch in a silent atmosphere. While watching the contents, learners' Beta brain waves are recorded and a dataset is created at an interval of one second.

IV. EXPERIMENTATION-1

A. PROPOSED BIO INSPIRING CHATBOT METHOD

The proposed Chatbot questions are simple and are of one line questions. The loop of the questions are divided into three parts like,

1. Learners likes and dislikes (Colors)
2. Day to day unique habits (Coffee / Others)
3. Learning preferences on learning (Individual / Group Learning)

The design of the Chatbot [66] consists of three parts. They are Natural Language Processing (NLP) [67], Natural Language Understanding (NLU) and Decision Making Engine (DMG). NLP is generating answers or queries from the Chatbot. NLU is getting the meaningful data extraction from the user's input. DMG is to perform the binary decision by the bot whether to respond or to wait. The database stores all the conversations made between the Bot and the learner.

The data flow of the proposed Chatbot and the basic principle of the Chatbot is given in Figure 4. It relates the possibility of questions from the Bot, possibility of answers from the respective learner and the vice versa. The questions and the respective answers the learners give are used to classify the learners into Extraverts or Introverts. At the end of the chat, the classification can be done using Chatbot. The experimentation of Chatbot is conducted for different age group of learners. The Chatbot's Unified Resource Locator (URL) link [49] is shared with 118 learners from SRM Institute of Science and Technology, Kattankulathur, Chennai, India. As per the data flow of the proposed Chatbot, the implementation is performed using Land Bot online tool [49] which is a tool for creating online interfaces for Chatbot. The principle of the proposed system is based on drag and drop method.

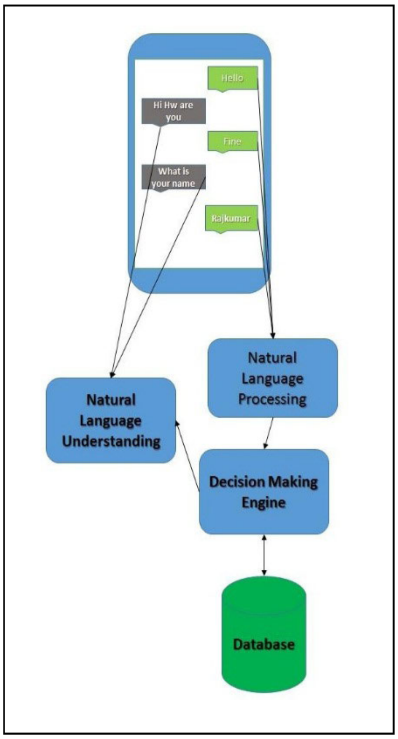
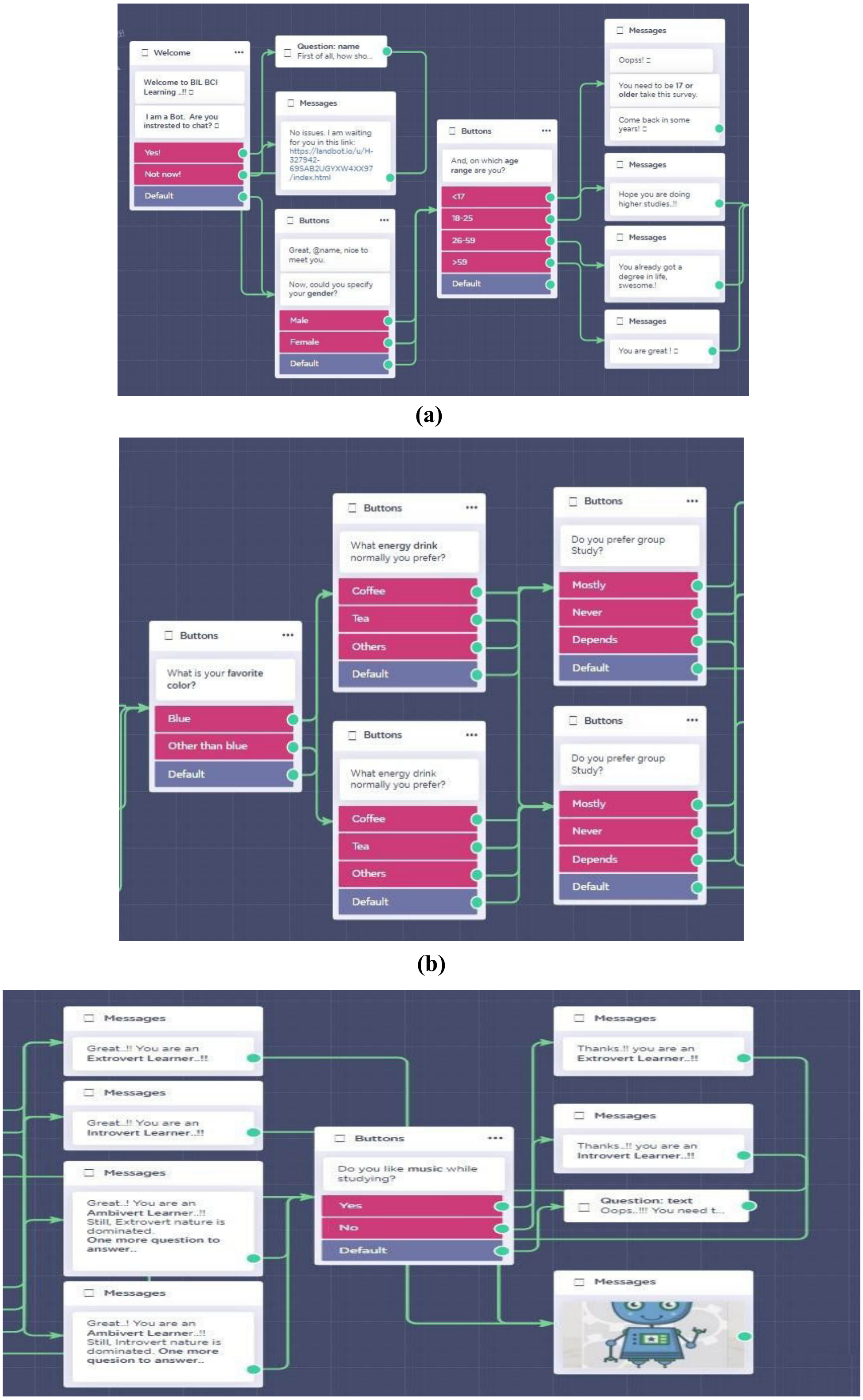


FIGURE 4. General architecture of chatbot [66].

Initially learners are divided into groups based on their age. After the interaction with the Chatbot, the learners are



(a)

(b)

(c)

FIGURE 5. **Chatbot – basic information gathering (b) Chatbot – learning preferences information gathering (c) Chatbot – bio inspired learning style information gathering.**

classified into Introvert, and Extravert. Table 5 shows the total population of the learners divided based on the age group.

Figures 5(a), 5(b) and 5(c) describe the overall design of the proposed Chatbot.

TABLE 5. Age group of learners in experimentation.

SI.NO	AGE GROUP	COUNTS
1	< =17	0
2	18- 25	70
3	26- 59	46
4	> 59	2
5	**Total**	**118**

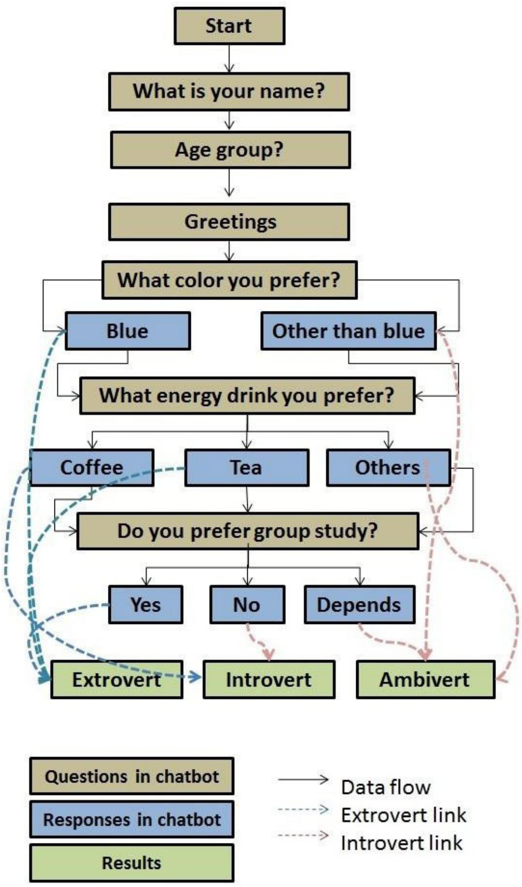


FIGURE 6. Data flow of the proposed bio inspired chatbot.

Figure 6 shows the data flow diagram for the proposed Bio Inspired Chatbot. The concept of the Chatbot is derived from the work "Bio-Inspired blood group prediction" [63]. The motivation of the Bio-Inspired Chatbot is to take well deserved answers from their learners' day to day activities. There is an undo option at the conversation table itself if the learner has wrongly typed the responses.

The Chatbot interacts with the learners and each learner is allowed to take his/her own time to complete the interaction with the Chatbot. Some of the learners do not fit into Introvert or Extravert. These kinds of learners are classified as Ambiverts. The Ambiverts are having both the features of Extraverts and Introverts. Each of the 118 learners takes different times when he or she interacts with the Chatbot. The average time taken by the learners is 3.53 minutes to interact with the Chatbot.

Figure 7 shows the screen shots of the actual implementation for the proposed Chatbot that can be opened in any mobile device browsers or desktop PC browsers.

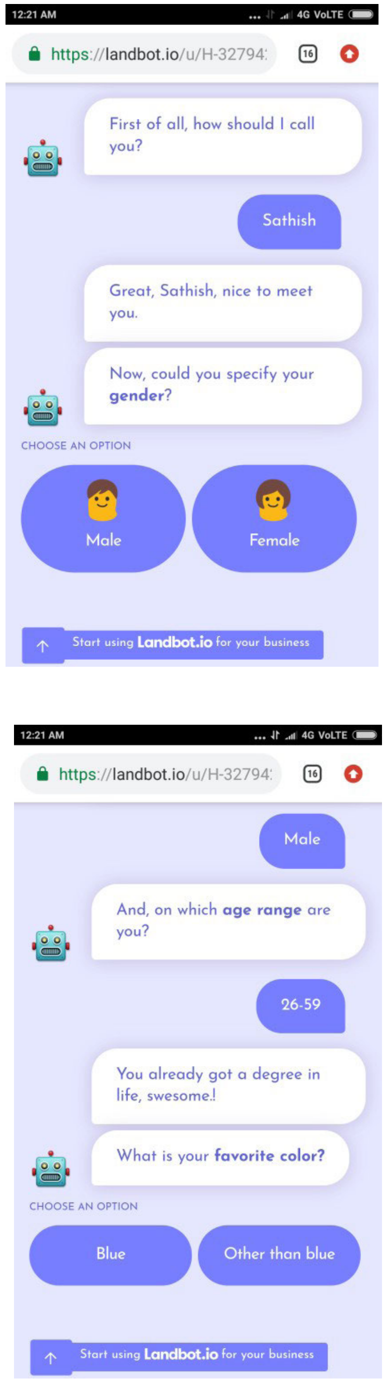


FIGURE 7. Mobile screen shot images of the proposed chatbot.

Table 6 shows the final classification of the 118 learners after they have interacted with the proposed Chatbot.

Figure 8 shows the visualization on Chatbot Classification of 118 learners.

TABLE 6. Final classification of learners using the proposed chatbot.

SI.NO	CLASSIFICATION	COUNTS	Average time taken
1	Extraverts	56	3.53 minutes
2	Introverts	47	
3	Not to classify (Ambiverts)	15	
	Total	118	

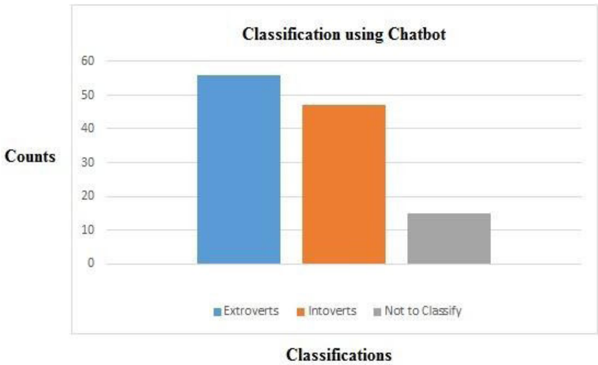


FIGURE 8. Classification of 118 learners.

V. EXPERIMENTATION-2

This experimentation is to classify the learners into three groups (Introvert, Extravert and Ambivert) by Brain Computer Interface. The learners are seated in a silent atmosphere. As per the international guidelines [59] learners are requested to take a long breath for at least ten times before they are allowed to record their brain EEG Signals.

The learners participated in this study students and staffs are from SRM Institute of Science and Technology located at Kattankulathur, India. A total of 118 healthy learners are chosen for this experiment in the age groups between 18 and 79 years. They are requested to watch the sample audio and video learning contents [60]. The common learning style course contains Visual and Auditory contents. As shown in Figure 9, the visual major content is shown for the first 60 seconds and the auditory major contents are shown for another 60 seconds continuously for a total of 120 seconds.

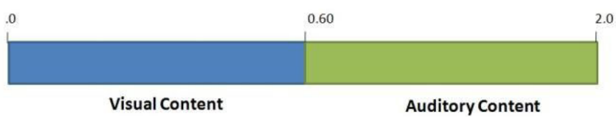


FIGURE 9. Timelines for the multimedia content.

The Neorosky EEG Sensor is placed at the forehead of the learner. Once the learners calm down themselves the testing sample contents are shown to the 118 learners. While watching the sample Audio Visual content, each learner produces Beta waves at one second interval continuously. The data is time dependent. The learners produce Beta waves with respect to the sample contents shown to them. The EEG brain waves are recorded for 122 seconds duration of which the first and the last seconds are for starting and stopping the record of EEG signals using EEG BCI Sensor. The dataset consists of 118 rows (118 Learners) and 122 columns (122 Seconds) amounting to 14,396 entries.

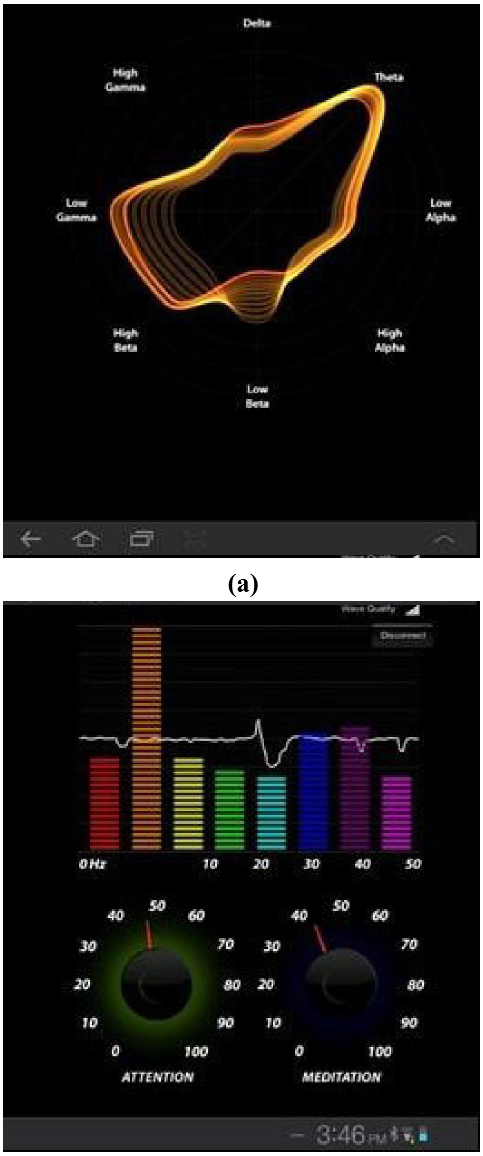
Figure 10 shows the experimental setup in which learners are tested with BCI Device while showing the visual and auditory contents to them.

FIGURE 10. Learners are tested with BCI device for the experimentation-2.

It is observed that every learner had produced a unique EEG brain wave. During the testing, the Introvert's Beta waves are of low amplitude whereas the Extraverts produce high amplitude Beta waves when the same auditory contents were continued to be shown to them. Ambivert [23] is a classification which is a combination of Introvert and Extravert. From these patterns, it is possible to classify the learner into Introvert or Extravert or Ambivert.

Figure 11(a) Visualizes the EEG waves like High Alpha, Delta, Theta, Low Alpha, Low Beta, High Beta, Low Gamma and High Gamma. Meditation (Theta) and Attention (Beta) measurements are shown in the Figure with 0-100 range. Figure 11(b) shows the visualization of metrics of attention and meditation in EEG brain waves.

It is clear from Figure 12 that Introverts produce a high magnitude of Beta waves during the initial period when the visual contents are shown, whereas the Extraverts produce low amplitude Beta waves during the initial period when



(a)

(b)

FIGURE 11. visualization of brain waves (b) Metrics on attention and meditation.

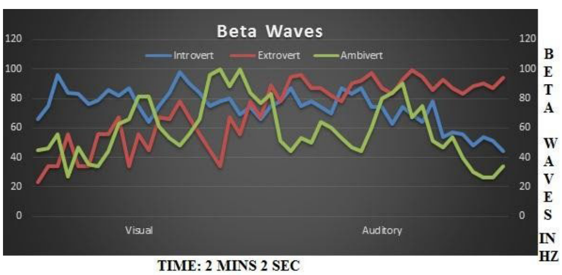


FIGURE 12. Beta waves of random learners.

the visual contents were shown. Ambiverts produce lesser modulated Beta waves during the entire testing period.

The EEG brain waves have quite large variations. EEG brain wave datasets are to be normalized before proceeding for classification. The EEG brain waves should be normalized without affecting their original data values. The highest modulated frequency is 16776448 Hz which is represented as an 8 digit number. Initially the frequencies have to be converted into digits in the given range.

The proposed normalization is given in the following steps:

Pseudo Code:
Read x
If (x <= 999)
Set x to 1;
Else if (x <= 99999)
Set x to 2;
Else if (x <= 999999)
Set x to 3;
Else
Set x to 4; End

The proposed approach for normalization is applied to 14,396 (118 x 122) Beta wave entries of the dataset. The new variables x1, x2, x3 and x4 are introduced after normalizing the large numbers as shown in Table 7.

TABLE 7. Normalization of beta waves.

Beta waves Range	After normalization
Above 999999	x4 (4)
100000 - 999999	x3 (3)
1000- 99999	x2 (2)
0 - 999	x1 (1)

The proposed BCI method uses WEKA 3.8.3 version which is utilized for classification of learners using machine learning algorithms. Waikato Environment for Knowledge Analysis (WEKA) [61] is a data mining tool. It contains a large number of machine learning algorithms. It is widely used for research, teaching, and commercial applications of Machine Learning.

WEKA is developed at laboratories of the University of Waikato, New Zealand. WEKA is free software licensed under the GNU General Public License. There are 55 classification algorithms available in WEKA tool.

Since the data sets generated are time dependent data, and hence Naïve Bayes and J48 classification algorithms are applied to the proposed data sets. The datasets and a confusion matrix are formed. Following Table 8 shows the details of input elements applied to the WEKA tool.

TABLE 8. Input elements applied to the WEKA Tool.

Value	Count
Total	14,396
Minimum Value	1
Maximum Value	4
Mean	2.407
Standard Deviation	1.262

A. A CLASSIFICATION USING Naïve BAYES CLASSIFIER

Naïve Bayes [62] is an easy and fast algorithmic tool to predict classes of test data set. It also performs well in multi class predictions. In this cross validation method, the algorithm is run for *n* times where *n* is the number of data sets. In each run, one of the instances is used as the test data and the remaining instances are used as the training sets.

Algorithms steps:

INPUT: Data Set
OUTPUT: Accuracy of Classification

```
BEGIN
{
    Set correctClassificationCount to 0
        FOREACH DataInstance Di in DataSet
        {
        SET TestData = Di
        SET TrainingSet = DataSet.RemoveAt(i)
        CALL TrainClassifier with TrainingSet
        CALL ClassifyTestData with Ti
        IF classification = Ti.Class THEN
        INCREMENT correctClassificationCount
        ENDIF
}
```

Here, Di = Data i, Ti = Time I

While,

P ((Learner / (Extravert and Introvert))

*= [P (Introvert | Learner) * P(Extravert | Learner) * P(Learner)] /*

*[P(Introvert) *P(Extravert)]* — [62]

The BCI dataset of 118 learners is applied to the Naïve Bayes classification algorithm available in WEKA tool. Time taken to build the model is 0.06 seconds. Table 9 shows the summary of the results when Naïve Bayes classification algorithm is applied for the datasets. Table 10 shows the confusion matrix for the datasets of Naïve Bayes classification.

After applying the Naïve Bayes classifier to the data sets, the confusion matrix is created. It is found that 50 learners belong to Extravert, 48 learners belong to Introvert and 12 learners belong to Ambivert. (8 instances are not classified.)

TABLE 9. Summary of results after running the data sets for Naïve bayes classification using WEKA tool.

Parameters	Values
Correctly Classified Instances	110 (93.2203 % Accuracy)
Incorrectly Classified Instances	8 (6.7797 %)
Kappa statistic	0.8872
Mean absolute error	0.0452
Root mean squared error	0.2126
Relative absolute error	11.36%
Root relative squared error	47.73%
Total Number of Instances	118

TABLE 10. Summary of results after running the data sets using Naïve Bayes classification of WEKA Tool.

a	b	C	Classified as
50	3	3	a = E
0	48	0	b = I
0	2	12	c = A

B. CLASSIFICATION USING J48 CLASSIFIER ALGORITHM

Decision tree J48 is the implementation of algorithm using Iterative Dichotomiser (ID-3) developed by the WEKA project team.

TABLE 11. Summary of results after running the data sets for J48 classification using WEKA Tool.

Parameters	Values
Correctly Classified Instances	112 (94.2203 % Accuracy)
Incorrectly Classified Instances	6 (5.0847 %)
Kappa statistic	0.9153
Mean absolute error	0.0595
Root mean squared error	0.1724
Relative absolute error	14.94%
Root relative squared error	38.71%
Total Number of Instances	118

The J48 is specially made for dataset with a list of targets and dependent variables. Inputs are 1(×1), 2(×2), 3(×3) and 4(×4); Targets are Introvert, Extravert.

Here,

D = Dataset

A_{Best} = Best Attribute

D_v = Induced Sub Datasets

$Tree_v$ = Tree (J48)

J48 classification algorithm is applied to the data sets in the default setting of the algorithm. The dataset has input elements like 1, 2, 3 and 4. Table 11 shows the parameters after executing the classification. The result is used to get a confusion matrix for J48 classification.

Time taken to build the model: 0.06 seconds.

Steps or Pseudo code for J48 Classification Algorithm:

```
Input: a dataset D
begin
  Tree = { }
  If (D is "pure") || I(other stopping criteria met) then
                                        terminate;
  For all attribute a a ∈ D D do
     Compute criteria of impurity function if we spit on a;
  a_best = Best attribute according to above computed
                                        criteria
  Tree = Create a decision node that tests a_best in the root
  D_v = Induced sub-datasets from D based on a_best
  For all D_v do
     begin
       Tree_v = 148 (D_v)
       Attach Tree_v to the corresponding branch of Tree
     end
  return Tree
end
```

Table 12 shows the confusion matrix, when data sets are applied to the J48 classification. In that, 52 learners are classified as Extravert, 48 learners as Introvert, 12 Learners as Ambivert, and then 6 learners are not classified into any category.

TABLE 12. Confusion matrix for J48 classification algorithm.

a	B	C	Classified as
52	1	3	a = E
0	48	0	b = I
0	2	12	c = A

Figures 13(a) and 13(b) are the visualization of Naïve Bayes and J48 algorithm using WEKA Visualization.

C. CLUSTERING USING CANOPY ALGORITHM

For grouping objects into clusters, an accurate method that can be employed is Canopy clustering algorithm. In this method, multidimensional feature space is used to represent all objects as a point. In this, two distance thresholds T1 and T2 and a fast approximate distance measure are used for fast processing. The basic algorithm is to begin with a set of points and remove one at random. To begin with, consider a set of points and remove one point at random. Create a Canopy containing this point and iterate through the remainder of the point set. A Canopy is created at each point and if the distance from the first point is < T1, then add that point to the cluster. The point is removed from the set if the distance is < T2. This procedure will avoid all the points that are very close to the original points. The algorithm keeps running till the initial set is empty and accumulating a set of Canopies, each containing one or more points. One point can occur in more than one Canopy.

In the initial steps of the canopy algorithm, use of more rigorous clustering techniques, such as K-Means Clustering, will be found to be of much use. By starting with an initial clustering and by ignoring points outside of the initial canopies, the number of more expensive distance measurements can be significantly reduced

The algorithmic steps are described as given below. The steps to execute the algorithm using two thresholds T1, defined as the loose distance and T2 defined as the tight distance are as shown in the following procedure.

1. To start with, collect the set of data points that are to be clustered.
2. Begin a new canopy by adding a point from the set.
3. Each point is assigned to the new canopy of the remaining points in the set.
4. If the distance of the point T1 is less than the tight distance T 2, remove it from the original set.
5. Until there are no more data points in the set to cluster, keep repeating fromstep-2.
6. The clustered canopies can be sub-clustered using a more accurate algorithm though expensive.

Table 13 shows the summary of the specifications created by of Canopy Clustering algorithm using WEKA Tool.

TABLE 13. The summary of results for clustering.

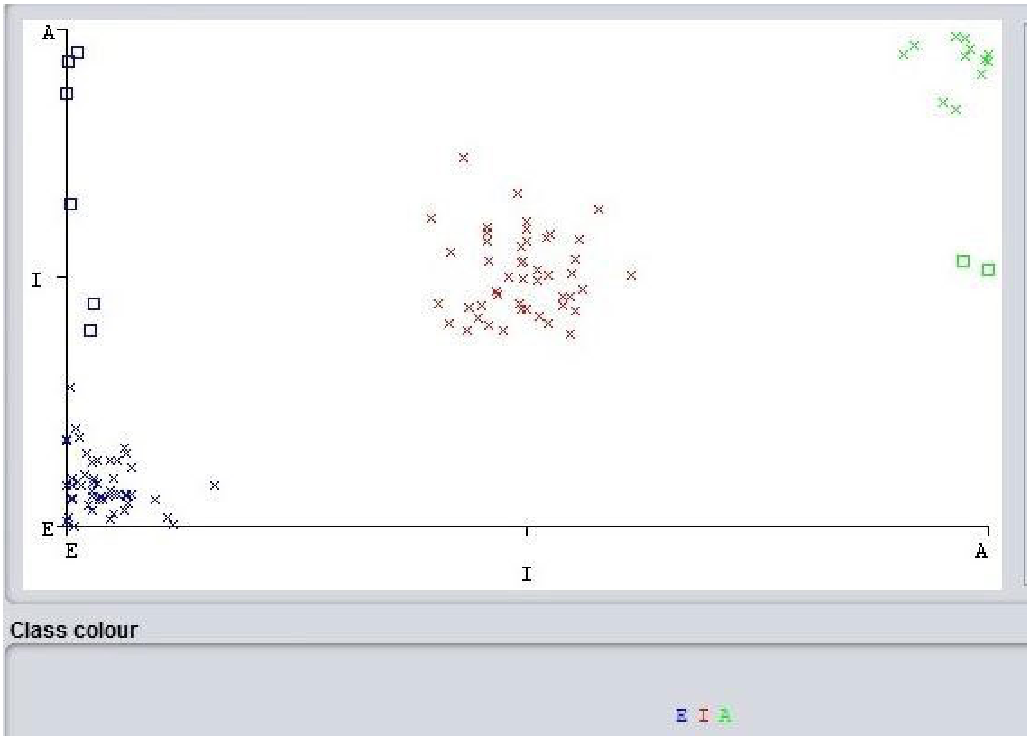
Number of Canopies found	3
T2 radius	4.597
T1 radius	5.746
Time to build the model	0.13 Seconds

Figure 14 shows the visualization of the clustering performed by the Canopy algorithm.

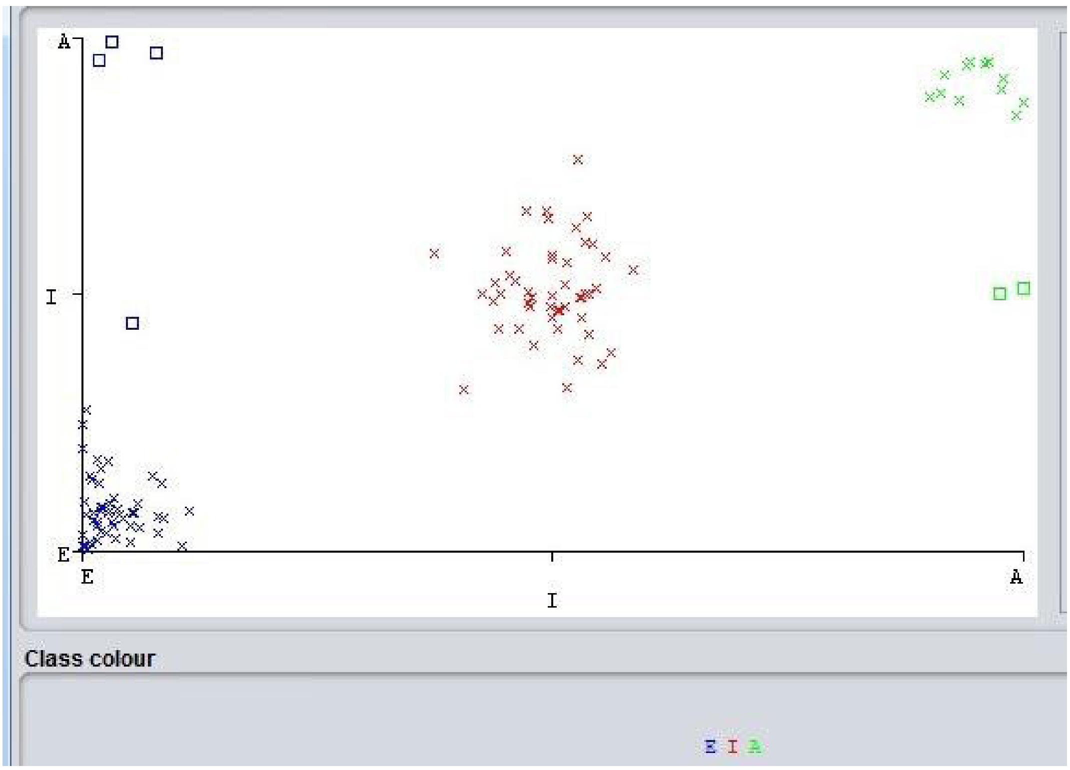
In table 14, the clusters are divided into three clusters consisting of 45%, 42% and 13% of data from the given datasets.

TABLE 14. Cluster instances applying by canopy clustering algorithm.

Clusters	Total numbers
0	53 (45 %)
1	50 (42 %)
2	15 13 %)



(a)



(b)

FIGURE 13. Visualization of Naïve bayes algorithm classification (b) Visualization of J48 algorithm classification.

In this, it is 45% of the data applicable to Extraverts, 42% data to Introverts and 13% data to Ambiverts or unclassified learners.

VI. RESULTS

Experiment-1 performed has classified the learners into Introverts, Extraverts and Ambiverts. Experiment-1 has a modified

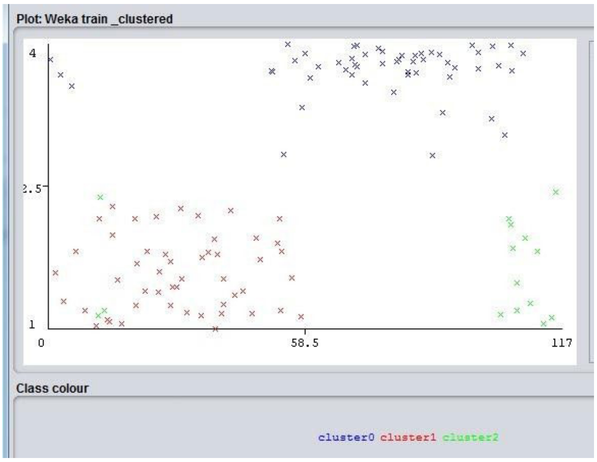


FIGURE 14. Visualization of canopy clustering.

TABLE 15. Comparison table between proposed method and machine learning classification.

Algorithm / Parameter	Proposed Bio-Inspired Chatbot Method	Naïve bays Classification Algorithm	J48 Tree Classifier Algorithm
Accuracy	NA	93.2203%	94.9153%
Time taken to build model	NA	0.06 Sec	0.01 Sec
Classification	E -56 * I -47** A -15***	E - 53* I -48** A - 14***	E - 52 * I - 48 ** A - 12 ***
Not Classified	Nil	8	6

*Extroverts ** Introverts ***Ambiverts NA – Not Applicable

VARK questionnaires and it is implemented as a Chatbot to classify individuals as Introverts or Extraverts or Ambiverts. The Questions are simple and effective for classification. The concept of the Chatbot is derived from the work "Bio-Inspired blood group prediction" [63]. The motivation of the Bio-Inspired Chatbot is to take well deserved answers from their learners' day to day activities. The Chatbot is a decision making tree which starts with easy questions of learners' day to day life activities and finally end up with identifying themselves as Introverts or Extraverts or Ambiverts.

Experiment-2 has applied machine learning algorithms taking EEG BCI signals as input and Classification as output and Clustering processes are performed using WEKA Tool. The EEG BCI signals are found to be most reliable signals. The comparisons between the proposed Bio-Inspired Chatbot method and machine learning classification are shown in Table 15. In addition, the results of comparisons between the proposed Bio-Inspiring Chatbot method and Canopy clustering are shown in Table 16. From the results it is clear that the proposed Bio- Inspiring Chatbot has given higher accuracy in classification than the existing online learning style inventories.

VII. FINDINGS

In this study, the classification of Visual learner or Auditory learner is based on the neuronal responses recorded during the

TABLE 16. Comparison table between the proposed method and Canopy Clustering.

Algorithm / Parameter	Proposed Bio-Inspired Chatbot Method	Canopy Clustering Algorithm
Time taken to build model	NA	0.13 Seconds
Classification/ Clustering	E - 56 * I - 47** A - 15***	E - 53* I - 50** A - 15***

*Extroverts ** Introverts ***Ambiverts NA is Not Applicable

information retrieval tasks combined with Brain Computer Interface and the machine-learning algorithm, rather than using VARK questionnaires. However, classification among Introvert and Extravert personality traits using Chatbot takes less time than the existing systems. The classification accuracy of the Chatbot is similar to Brain Computer Interface using machine learning algorithms. Table 17 shows the findings and recommendations to the E-Learning content developers to prepare customized E-Learning course contents.

TABLE 17. Recommendations for customized E-Learning.

S.No	Learning styles	Contents
1	Introvert Learners	Diagrams, Images, Charts, Visual Presentations, Animations, No Groups.
2	Extravert Learners	Audio books, Music, Presentation with audio, Group study,

VIII. DISCUSSIONS

There are many classification algorithms available for machine learning. But it has been a difficult task to choose the best one as the selection depends on the application and nature of data set.

In the experiments conducted, the BCI data set is time dependent. In the experimentation, out of 118 instances, Naïve Bayes algorithm has classified the 118 instances into three groups classifying only 110 instances and leaving out 10 instances, whereas J48 algorithm has classified the 118 instances into three groups again but classifying 112 instances and leaving out only 6.

In the experiments conducted, the accuracies of the Naïve Bayes classification and J48 classification algorithms are more than 90 percent. Sometimes it is construed that the dataset might have been over fit if the efficiency is higher. However, in this case, it has been proved that the accuracies obtained are valid by subjecting the algorithms to clustering. To authenticate the accuracy of the classification, researchers suggest [69] to use unsupervised machine learning methods.

IX. LIMITATIONS

The proposed framework has a few limitations. The 118 learners sample size is not enough to predict the learning style of the entire learners in E-Learning. However, in future studies can be conducted with more number of leaners to classify them into their proper learning styles. In addition, these experiments investigate the learning styles of introverts and extraverts learners only. There is one more personality trait called Ambiverts. In future, the Ambivort learning style should also be taken into account. Also, EEG is the only modality that is used for the experiment. The other learning assessment parameters like facial expression, body language and sign language also may be included to improve the efficiency in real time customized E-Learning.

X. CONCLUSION

E-Learning researchers are utilizing machine learning techniques to understand the learners' behaviours. There are different approaches that exist about the classifications of learning styles. Neil Fleming's VARK questionnaires are used by many researchers to classify the learners based on their learning preferences. Swiss psychoanalyst Carl Jung explored that Introverts and Extraverts are the personality traits among the human beings. Korean researcher Soomin Kim's study [64] shows that Chatbot can be a promising method of gathering quantitative data. The proposed research work in this paper is to find out the correlations between Introvert, Extravert personality types and their corresponding learning styles. Initially, modified VARK questionnaires are implemented as a Chatbot to classify individuals as Introverts or Extraverts. The Chatbot participant's responses are found to produce high-quality data. After the classifications from the Chatbot, two minutes of Visual and Auditory contents are given to the learners to watch in a silent atmosphere. While watching the contents, learners' Beta brain waves are recorded and a dataset is created at an interval of one second. This dataset is validated using machine learning classification [65] algorithms like Naïve Bayes, N48 tree and Clustering algorithms. It has been observed that, the proposed method has given improved accuracy for classification of Learners. The proposed Bio Inspired Chatbot takes less time for classification of learners than the existing methods. Bio-Inspired Learning style Brain Computing Interface (BIL-BCI) framework is a recommendation system for E-Learning content developers to classify the learners into ''Introvert-Extravert learning style inventory'' to deliver Auditory and Visual learning contents. The BIL-BCI framework can be exported to mobile platforms and other smart devices for ease of using it for further experimentations.

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