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Multidisciplinary Review on Brain Computer Interface Based EEG for Assessment of Emotion Recognition System and Cognitive States During Learning Activities.

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Abstract: Brain-Computer Interface (BCI) associations the human's neural world and the outer physical world by interpreting individuals' brain signals into commands detectable by computer devices. In this technology the noninvasive BCI technique that is electroencephalography plays a vital role for acquisition of brain signals and developing Emotion Recognition System .The Emotions are very important in our life for interaction, decision handling and cognitive process. Whereas in recent years, increasing studies have employed many technologies to monitor students' cognitive states and attempted to provide adaptive interfaces and contents accordingly to improve learning efficiency of students. This study covers the review on brain signal acquisition techniques, Classification techniques, basic functioning of brain and comprehensive survey on EEG–Based BCI system for Emotion Recognition and also to review the learning activities and the parameters involved in estimating the cognitive state. According to this study gives the conclusion like Support Vector Machine classification techniques is most preferred by the various researchers for analyzing the emotions and also various authors has done the work on various learning fields such as Mathematics, Engineering, Programming and Medical helps to assess the cognitive states like memory, engagement, mental workload , attention etc. at National and International level.
Keywords: Brain Computer Interface , Electroencephalography ,Emotion Recognition System ,Cognitive States ,Learning Activities.

I. INTRODUCTION

Brain Computer Interface work is emerging field since past few years[1].EEG is a non-invasive technique consist of alpha ,beta ,delta and gamma signals and it has many novel applications that are crucial to people's daily life[2]. Emotion detection is one among the growing areas in affective-computing field where the interaction between machines and individuals can be improved through the change in individual's inner states. Emotions are complex phenomena which play an important role in human quality of life. In motivation, cognition, perception, attention, creativity, learning and for decision-making everywhere emotion plays a major role[3]. Breaking down and evaluating feelings has become a significant Multidisciplinary study point in the various domain such as neuroscience ,brain research, intellectual science, software engineering, and computerized reasoning. [4][5].Whereas the research area Cognition is one of the important domain in neuroscience field. A cognitive state is the mental action of acquiring knowledge through thoughts, experience and senses. There are various processes and functions that contribute to a cognitive state or skills such as attention, working memory, reasoning, Engagement, Perception, problem solving, and so forth. Psychological efforts means the cognitive actions Executed to complete a task. In cognitive psychology the term cognitive load refers to the used amount of working memory resources [6][7]. The cognitive skill focused attention means all subjects' activities involve active cognitive processes such as problem-solving and critical thinking .whereas the state working memory is a type of short-term memory that allows subjects to store and manipulate temporary information[8].These cognition skills are plays very crucial role in human's life, such as decision making , learning .During the learning process whether students are attentive when learning significantly influences their learning outcomes[9][10].The ability to measure the student's cognitive skills during instruction is essential as they provide valuable feedback to the instructor whether the learning goals have been achieved and to identify the type of intervention needed to improve learning and cognitive states outcomes [11]. So this need is led to the growing interest using psycho-physiological Brain Computer Interface (BCI) systems to collect and analyze signals using EEG from the human brain to determine its cognitive state during learning activity [12].The goal of this study is to study the previous work and find out appropriate emotion identification features through various imaging techniques, and also need to find out which automated classification model used to identify and enhance emotion classification efficiency. Further objective is to classify the best significant frequency bands and brain areas for Emotion Recognition activities and contribute the EEG-based Emotion Recognition

Research with a strong physiological basis. And also this study Covering the part relates to cognitive state estimation with respect to learning using Brain Computer Interface based EEG.

II. BCI FRAMEWORK AND TYPES OF BCI SYSTEM

A) BCI Framework

The basic components required for implementation are depicted in Figure 01 .The BCI framework divided into different modules such as Signal Acquisition, Signal Processing, Feature Extraction, Classification and Command Generation modules .

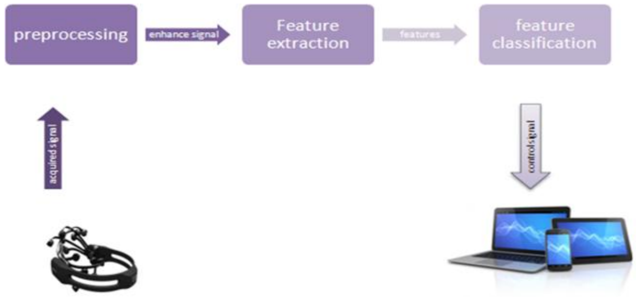

Figure 01 .The BCI framework

B) Brain Computer Interface System categories in to following types.

2.1 Invasive / Non-Invasive BCI System

The Brain Computer Interface systems are commonly known as invasive and non-invasive. In invasive type BCI system Microelectrodes are implanted inside the skull of the user's. Like ECoG. On the other hand, the non-invasive form of BCI device requires the monitoring of electrical brain activity by placing the electrodes on the scalp. Such as Electroencephalography (EEG). So, EEG-based BCI systems are being widely used [13] [14].

2.2 Synchronous / Asynchronous BCI System

The synchronous type of BCI system is cue based which means the user produces particular mental states by doing certain mental task in a predetermined time period. Here the control is system-initiated. Whereas the asynchronous type of BCI system is un-cue based. Here, the user is free to initiate any particular mental task which is considered as control signal. So, the control is user-initiated, not system-initiated [13] [14][15].

2.3. Universal / Individual BCI System

In universal BCI systems, the EEG data is collected from various users to find features and classification method which is suitable to any person. Using individual BCI system the EEG data is collected from individual user keeping in mind that no two individuals are same. So, every BCI system is different Therefore, this type of BCI system is different with different users [13] [14].

2.4. Offline / Online BCI System

In offline BCI system the EEG signals are recorded as in online BCI using more electrodes. These recorded EEG signals are stored and used later to develop the BCI systems or for actual BCI research. Where, the online BCI systems are the actual real-time working systems which provide feedback for the user. This is not possible in the offline BCIs systems [13] [14].

2.5 Imagery / Mental Task BCI System

The imagery BCI systems are from the user's point of view i.e. Depending on the type of imaging function that users are required to perform like motor imagery. Mental tasks BCI system involves arithmetic task like visual counting task and visual task like Geometric figure rotation etc [13] [14].

2.6. Exogenous / Endogenous BCI System

The Exogenous BCI systems are evoked that is dependent on stimulus which requires minimal training whereas the Endogenous BCI Systems are self-generated that is independent of stimulus for e.g. cursor control applications [13][14].

III. BRAIN IMAGING TECHNIQUES

There are number of brain imaging techniques which can be categorized as: structural or anatomy, functional or electrophysiology and molecular.

1) Structural or Anatomy neuro-imaging: to visualize the Brain Structure[13][4][16].

Table I. Structural Brain Imaging Techniques

Technique	**Advantages**	**Disadvantages**
X-ray	Cheaper than other techniques	Invasive, Uses ionizing radiation, harmful to body, Less amount of information

Angiography	Gives detailed information	Invasive, Use X-rays
CT scan(Computed Tomography)	Non-invasive, Short procedure	Do not show functions of the organ, Uses x-rays
Ultrasound	Non-invasive, Less expensive Quick and painless	Heavily operator-dependent
MRI(Magnetic Resonance Imaging)	Non-invasive, painless, No use of X-rays or radioactive material	Expensive, Do not show functions of the organ, Not applicable for the patients with metallic devices, like pacemakers

2 . Functional neuro-imaging: used not only to visualize but also for imaging the functions of the brain. There are mainly two categories: hemodynamic or physiological and electro-magnetic technique or electrophysiological imaging technique.
i) Hemodynamic or Physiological Imaging Techniques: used to detect and measure the changes in brain metabolism [13][14][16].

Table II. Physiological Imaging Techniques

Technique	**Advantages**	**Disadvantages**
PET scan(Positron Emission Tomography)	Shows brain functions	Expensive, Invasive
SPECT(Single Photon Emission Computed Tomography)	Less Expensive	Invasive, Limited resolution
fMRI(Functional magnetic resonance imaging.)	Non-invasive, Shows excellent resolution of brain activity	Expensive, Lengthy procedure, Not applicable for the patients with metallic devices, like pacemakers

ii) Electro-Physiological or Electro-magnetic Imaging Techniques: used to detect and record the brain cell's electrical activity directly [13][14][16].

Table III. Electro-Physiological or Electro-magnetic Imaging Techniques

Technique	**Advantages**	**Disadvantages**
EEG(electroencephalography)	Non-invasive, Inexpensive	No images, only brainwaves, Poor resolution
MEG(Magnetoencephalography)	Non-invasive	Expensive, Poor availability
ECoG(Electrocorticography)	Good resolution	Invasive

3) Molecular Imaging Techniques: used to detect the biochemical activities of cells or molecules in human body or animals [13][14][16].

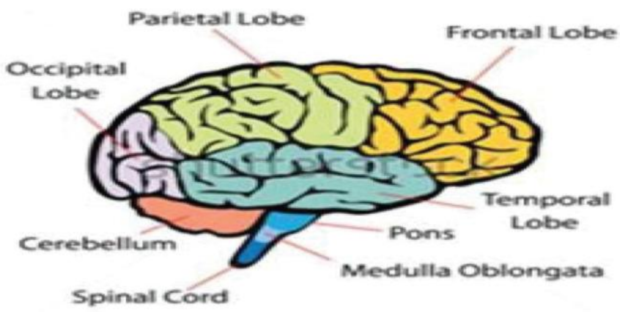

Figure 02 : Sections of the Brain

III.A) Brain and Its Functions The brain also called the nervous system is a integral factor of the human body. It controls the human body and performs various functions like cognition, perception, attention, memory and emotion. It consists of 100 billion neurons where each neuron is linked to approx. 10,000 more neurons. The neuron is the basic element of the brain which is electrically active [16].

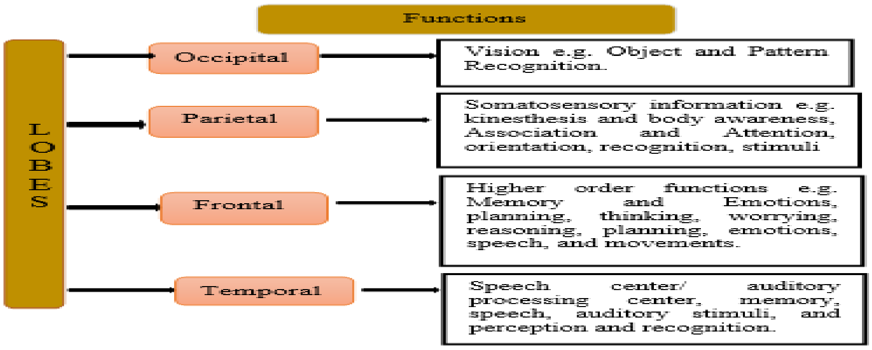

Figure 03 : Functions of Brain

IV) RELATED WORK

A)Emotions and models of emotion

Emotional states are correlated with a wide variety of human emotions, perceptions and behaviors, thereby influencing our ability to act rationally, in cases like decision making, perception and human intelligence. Emotions have a major effect on the social skills of a person and their perception of the world. Emotion is an individual, sensible experience when people face inner or outer stimuli that play an essential role in natural human communication. The following table shows the classification of emotions [16][17][18]. Scientists in numerous fields have proposed different strategies for the detection of emotion in recent decades. The numbers of EEG-based emotion detection research and publications have grow in current years. Different models and strategies yield a wide scope of frameworks. Those framework can however be easily distinguished due to differences in input, detection characteristics, temporal window, classifiers, number of participants and emotion model, respectively[19][20][21].

Table IV. Models of emotion

Models of Emotion		
General Emotions	The Discrete Model	Happiness, Sadness, Anger, Surprise, Disgust and Fear.
	The Dimensional Model	Valence –Arousal (VA), Pleasure-Arousal-Dominance (PAD).
Learning Emotions	1. Learning activities. 2. Learning 3. Learning process. 4. Instructional design. 5. Learning environment.	

Table v. Emotion Recognition Systems using EEG

Emotions	**Stimulus**	**Data Acquisition Device**	**Features Extracted**	**Classifier**	**Accuracy**
Confusion	Online courses video clips	Mindset with Fp1 channel	Statistic features of raw signals, attention proprietary, meditation proprietary, and five bands	Gaussian Naive Bayes	60%
Trajectory emotion changes	Movie clips	62 channel Quick Cap	Power spectrum feature, wavelet feature, and nonlinear dynamical feature, using PCA, LDA and CFS to reduce dimensions	Support Vector Machine	Up to 78.41%
Happy, Fear, Relax and	Audio clips	10-20 System	Power spectrum features	Fast Fourier Transformation	-

Memory related				Skewness	
Eye movement(Positive ,Negative and Neutral)	Eye movements Chinese Movie clips	62 electrode channels according to 10-20 electrode System.	Power spectral density (PSD) and differential entropy (DE)	Support vector machine with linear kernel	87.58%
Attention	Online learning con-tents	24 chan-nel of device Nexus-32	Linear features (time-domain anal-ysis, Hjorth param-eters,frequency-domain analysis) and nonlinear features.	CFS and KNN (Correlation-based Feature Selection and k-Nearest Neighbors)	80.84%
Mild depression	Facial expression pic-tures	128 channel Hydro Gel Geodesic Sensor Net	Eight linear features and nine non-linear features. Using feature selection method GSW based on CFS	Five Machine learning algorithms like Bayes Net	92.0% and 98.0%
Excitement, Meditation, boredom, and frustration(Valence and Arousal)	-	EEG Deep database	Common Spatial pattern, Higher Order Crossings, Hjorth parameters, time-domain statistics, EEG spectral power, wavelet entropy, and coherence analysis.(PSD features and pre-frontal asymmetry features.)	Deep Learning Neural Network	82.0%
Calm ,Excitement	eNTERFACE Workshop 2006 database(Images)	Biosemi Active 2 system	EEG frequency band power Asymmetry Peak frequency in alpha band Hjorth parameters Cross-correlation between EEG band powers	ANN,KNN,NB, Support Vector Machine with Gaussian Kernel	75.59%, 75.06% and 75.12%
Arousal, valence, liking, dominance, and familiarity	Music video clips	10-20 system	First Difference of IMF Time Series, First Difference of IMF's Phase, Normalized Energy of IMF.	LIB Support Vector Machine	69.10% for valence and 71.99% for arousal
Valence and Arousal	Videos	10,14,18 and 32 channels EEG.	Discrete wavelet transform	KNN	Valence-95.70%And Arousal-95.69%.
Calm,excited	Facial expression and eye movement	62 channel EEG	Mean value, Standard Deviation, Mean Absolute Deviation (MAD), Gray Level Co-occurrence Matrix (GLCM) features including Contrast, Correlation, Energy, Homogenity, Entropy, Geometric features including corners and eigen values from the EEG signals,PSD	Support Vector Machine	-
Happy, sad, exiting and hate	Music Videos	32 channel BioSemi	Gabor wavelet features and intrinsic mode	Support Vector Machine with	93.86%

		acquisition system	functions features	Genetic Algorithm	
Agitation, valence and domination	Movie,Images	10-20 System	-	Support Vector Machine	92.56%
Math,Relax	Images ,Video	Consumer-grade brainwave-sensing headsets	-	K-NN, Decision Tree,Supervised Vector Machine , Softmax Classifier	66.16% 60.36% 68.29% 73.42%
Arousal,Valence	Music Video	10 channel EEG System	-	PCA,SVM,KNN,ANN	90.8 % for arousal 90.6 % For Valence
Valence and Arousal	Video clips ,Audio	10-20 system	PSD	Support Vector Machine ,CNN	69.28% valence and Arousal 64%
Deap database ,Seed IV database	Video clips	32 channel EEG 64 ,channel eeg database	Statistical features, Power features and other features.	Support Vector Machine	74%, 86% ,72% & 84% for DEAP database and 79%, 76%,77% & 74% for SEED-IV database
Deap database ,Seed IV database(Valence,Arousal ,Dominance and Like	Video clips	32 channel EEG	Hjorth activity, Hjorth mobility, Hjorth complexity, standard deviation, sample entropy, and wavelet entropy (WE)	ST-SBSSupport Vector Machine	72% (DEAP) and 89% (SEED).
Valence and Arousal	Video	40 channel eeg	Signal framing,Frequency band power feature, Channels' Pearson Correlation Coefficient	Support Vector Machine ,LSTM	81.10% in valence and 74.38% in arousal,
Happy ,Terrible	Video clip	1/32 channel EEG	Energy Logistic Coefficients	KNN,NN,CN	-
Valence–arousal–dominance	Music Videos	10-20 system	Power spectral density	CapsNet,Multi band Feature matrix	0.6828, 0.6673, and 0.6725 in arousal, valence, and dominance, respectively

Valence,arousal ,dominance, and liking	Video	Biosemi ActiveTwo system(40 channel)	-	Adaptive Multilayer Generalized Learning Vector Quantization (AMGLVQ) algorithm,RF,SVM	62.98% 54.54% 55.77%
Anger, Sad, Surprise, Happy, and Neutral	Visual Stimuli	64 –channels EEG	Anger,Happy ,Sadness,Neutral ,Surprise and No emotion	BackPropagation Neural Network	95%
Sadness,Anger, Stress	Visual Stimulus	ECG	Sadness,Anger,Stress	Support Vector Machine	78.4% and 61.8%,
Joy,Anger,Sadness,Pleasure	Music	ECG,EMG,RSP,SC	-	Linear Dicriminant Analysis pLDA	95%
Happiness,Sadness,Neutral	Film	EEG	-	-	87.1%,90.3 %,84%
Happiness,surprise, anger, fear, disgust, and sadness	Pictures	10-20 EEG System	Statistical Based Features ,HOC-Based Features	Quadratic Discriminant Analysis (QDA), k-nearest neighbor, Mahalanobis distance, and support vector machines (SVMs	62.3% and 83.33%
Sadness,Amusement,Fear,Anger,Surprise	Movie Clips	EEG	-	MBP,KNN,DFA	92%,67%,78
Happy, surprised, satised,protected, angry, frightened, unconcerned, and sad	Audio and Visual Stimuli	Emotive Epoc	Fractal Dimension feature, statistical and Higher Order Crossings (HOC) features.	Support Vector Machine	90%
Mental Task	-	10-20 EEG System	-	Quadratic classifier based on MD classifier	98%
High Valence and Low Valence	Images	03 Electrode IAP System	ERP	Support Vector Machine	95%
Joy,Anger,Disgust,Surprise,Sadness,Fear	Video clips	10-20 System	P300	Bayesian Linear Discriminant Analysis	80.19%

IV. (B) COGNITION

A cognitive state is the mental action of acquiring knowledge through thoughts, experience and Senses. There are many processes and functions that contribute to a cognitive state such as attention, memory, reasoning, problem solving, and so forth. For assessment of cognitive states learning module plays very important role. In below section states the research work done by various authors at National and International level in this respective area.

IV.II ESTIMATION OF COGNITIVE STATES DURING LEARNING ACTIVITIES USING EEG.

Chris Berka , Daniel J. Levendowski , Michelle N. Lumicao et.al.,[2007] investigated the investigation of observing Electroencephalography(EEG) signs of engagement and workload which was gained and measured during execution of cognitive test.

Thanh A Nguyen , Yong Zeng ,[2010] utilized EEG to record designer's cerebrum electrical signs when s/he was chipping away at a design task. Six channels of the EEG signals were recorded, including Fp1, Fp2, Fz, Cz, Pz, Oz, in light of which the power spectral density for every EEG band (delta, theta, alpha and beta) was determined. The outcomes indicated that, for the given deign issue, the subject burned through more energy in visual deduction during the solution generation than that in arrangement assessment.

Yongchang Li , Xiaowei Li [2011] This investigation portray a framework dependent on an Electroencephalogram which gauges the three consideration levels and grouped by a KNN classifier dependent on the Self-Assessment Manikin model with 57.05% exactness

Adreas Fink , Daniela Schwab et.al ,[2011] researched two methodologies, for example, regardless of whether imaginative insight can be improved by methods for psychological and emotional incitement exercises and whether these mediations are related with changes of EEG alpha action.

Dan Szafir , Bilge Mutlu ,[2012]they draw on procedures from brain computer interfaces (BCI) and information from instructive brain science to plan versatile specialists that screen understudy consideration continuously utilizing estimations from electroencephalography (EEG) and recover reducing consideration levels utilizing verbal and nonverbal signals.

Ning – Han Liu , Cheng – Yu Chiang and Hsuan – Chin Chu [2013] perceived the understudies were mindful and oblivious during learning movement utilizing portable sensors. A support vector machine (SVM) classifier was utilized to compute and dissect these highlights to distinguish the mix of highlights that best shows whether understudies are mindful. In view of the analysis results, the technique proposed in this investigation gives a characterization precision of up to 76.82%. The investigation results can be utilized as a source of perspective for learning framework plans later on.

Kavitha P Thomas , A .P .Vinod ,[2013] the authors explore the effect of a neurofeedback put together BCI game with respect to the improvement of attention and intellectual abilities of healthy subjects and the trial aftereffects of this examination show that the proposed neurofeedback preparing model starts the player to extend his entropy scores, upgrade attention level and achieve higher focuses in the game.

Nanda Nandagopal, Vijayalakshmi R , et.al ,[2013] In this examination the authors presents a diagram of the utilization of such strategies to EEG information ,bringing together an assortment of methods containing complex network investigation , coherence ,common data ,inexact entropy ,computer visualization ,signal handling and multivariate procedures, for example, the one-way analysis of variance (ANOVA). This examination exhibits that the incorporation of these strategies empowers a profundity of comprehension of complex cerebrum elements that is unimaginable by different techniques just as permitting the ID of contrasts in framework intricacy that are accepted to underscore typical human insight.

Hyunjeong Lee ,[2013] ,This investigation inspected a solid and legitimate technique for surveying psychological burden during learning through looking at different kinds of intellectual burden estimations: Electroencephalography (EEG), self-announcing, and learning result.

Geeta U .Navalyal , Rahul D .Gavas , [2014], point of this investigation is to detail a technique with the assistance of Brain Computer Interface game to help the coaches in noticing and assessing the attention levels of the students ,at normal intervals during the preparation time frame. For this examination reason the gaming climate is planned utilizing Open Source Graphics Library (OpenGL) package and the game control is through the cerebrum waves of player's utilizing the Brain Computer Interface (BCI) innovation.

Y .Liu , J.M .Ritchie ,et.al ,[2014] proposes and examines a system to decide the passionate perspectives credited to a bunch of CAD configuration undertakings by breaking down the CAD administrators' psycho-physiological signs. A fuzzy logic model was set up to plan the psycho-physiological signs to a set of key feelings, to be specific disappointment, fulfillment, commitment and challenge and the outcomes analyzed. Understanding of every participant's feelings were effectively completed with substantial connections showed between the related architects' CAD exercises and their detailed emotional states.

Niannian Wang , Li Zhang ,et.al ,[2015],they investigating the cognitive functions of the brain by making an network model to comprehend the working system of the brain has become an exceptionally famous exploration in point in the neuroscience field and in this examination electroencephalography (EEG) was utilized to gather information from subjects given four diverse numerical psychological errands: present numbers clockwise and counter-clockwise, and letters clockwise and counter-clockwise to fabricate a complex brain function network (BFN).

Poulami Ghosh ,Ankita Mazumder et.al [2015] the target of this investigation was to assess the cognitive state of brain. They concentrated in on memory and attention state. For this classification purpose they used Support Vector Machine and they acquired 79% classification precision.

Necmettin Firat Ozkan , Emin Kahya [2015] An investigation was directed with 30 participants. Every member finished two assignments through a BCI and filled NASA-TLX structures. The outcomes were examined utilizing combined t-tests to see whether BCI undertakings are altogether extraordinary regarding making cognitive load. The consequences of this investigation demonstrated that NASA-TLX scores of the BCI errands were essentially extraordinary and these frameworks can be considered for assessing cognitive examinations.

Patricia Soto-Icaza ,Francisco Aboitiz et.al[2015], Aim of this investigation was initially examine the improvement of social abilities in youngsters ,to explain the behavioral neural component identified with the obtaining of social aptitudes during earliest stages and their appearance as expected .Second they quickly depict how formative illnesses like Autism Spectrum Disorders(ASD) can educate about the neurobiological systems of social abilities. At long last they draw general system for the elaboration of cognitive models to encourage the perception of human social growth.

Xiaowei Li ,Martyn Ratcliffe et .al.,[2015]describe Real-time EEG – based BCI framework which estimates attention level. In this investigation they contrast their methodology and conventional methodologies, three consideration levels were ordered by a KNN classifier dependent on the Self-Assessment Manikin (SAM) model.

Fumihiko Taya ,Yu Sun ,et.al[2015] recommended that the learning cycle during the cognitive training can be encouraged by an assistive framework checking cognitive workloads with electroencephalography (EEG) biomarkers, and the brain connectome approach can give extra important biomarkers to encouraging leaners' learning measures.

Pouya Bashivan , Irina Rish ,et.al ,[2016], The authors observed reactions to two distinct sorts of input: instructional ('logical') versus recreational ('emotional') recordings, utilizing a scope of AI techniques. They attempted SVMs, sparse logistic regression, and Deep Belief Networks, to segregate between the perspectives prompted by various sorts of video input that can be generally marked as 'logical' versus 'emotional'. Their outcomes showed a major capability of wearable EEG gadgets in separating cognitive states between circumstances with major logical however unobtrusive clear contrasts.

Amit Desai [2017] gained the signs got from the brain are handled to quantitatively study and look at the brain exercises of coders while programming in two distinctive programming languages. In this exploration, they have picked the organized programming language C and the scripting language Python for examination.

Explored by Xi Liu , Pang – Ning Tan, et.al [2017],the possibility of utilizing EEG demos created from an off-the-shelf, wearable gadget to consequently characterize the cognitive conditions of students as they were approached to play out a progression of perusing and question noting assignments. They demonstrated that the EEG information can adequately foresee whether an understudy is mindful or occupied just as the student’s understanding rate, which is a significant proportion of understanding familiarity.

Raheel Zafar ,Sarat C.Dass et.al,[2017], In this examination, a novel calculation is proposed to interpret brain movement related with various sorts of pictures. In this hybrid algorithm , convolutional neural network is changed for the extraction of highlights, a t-test was utilized for the choice of critical highlights and probability proportion based score combination was utilized for the expectation of brain action. The strategies utilized in this examination were given the exactness like 65.7% and 79.9% separately.

Winnie K .Y.So , Savio W.H.Wong , et.al ,[2017] They researched the achievability of utilizing short term frontal EEG as a way to assess the dynamic changes of mental outstanding task at hand. In this examination subjects were performing four cognitive and motor tasks , including including arithmetic operation, finger tapping, mental rotation and lexical decision task. The degree of mental workload could be ordered from EEG highlights with 65%±75% precision across subjects utilizing a SVM model.

Richard W. Montgomery , Leslie D. Montgomery [2018], This paper depicts how ERP energy density examination and marginal cost-benefit analysis investigation were joined to understand the consequences of an examination of cognitive execution .They shows the cognitive presentation of each subject through four stages, for example, learning ,weariness, inspiration and weakness.

Author J.J.J.Davis , R.Kozma ,[2018] presented a cognitive modalities, for example, open eyes with visual stimuli, open eyes, close eyes, math problem solving and meditation. They demonstrated beginning proof that outer tangible information encourage neural movement in a scope of frequency bands, while self-initiated applied our film making procedure to subjectively investigate brain elements utilizing the art of encephalography in a novel way. In this current study we check the technology employing a 256 electrodes dense-array EEG established by EGI. The applied temporal and spatial Power Spectrum Density analysis is ready to categorize between these modalities.

Asma Ben Khedher , Imene Jraidi et.al,[2018] keen on breaking down the connection between students' visual behaviour and their exhibition while resolving clinical cases. Firstly they investigate how the students visually investigate the learning environment across various area of interest .Secondly observe whether static and dynamic eye tracking measurements can affect student' thinking execution.

In 2019 the authors saw a higher commitment list during the treatment identifictaion stage since it produced more mental exertion additionally statistically major impacts were found between metal engagement and students exhibition .This examination will valuable for comprehension of the student learning experience.

Muhammad Zeeshan Baig ,Manolya Kavakli [2019] They introduced a relative investigation of novice/expert data stream designs. Normalized Transfer Entropy (NTE) and Electroencephalogram (EEG)was used to examine the distinctions. The test was isolated into three cognitive states i.e., rest, drawing, and manipulation. They applied characterization calculations on NTE frameworks and diagram hypothesis measures to see the adequacy of NTE and accomplished over 90% exactness with a straightforward K-nearest neighbors (k-NN) to categorize novice and expert clients.

The authors Antoine Gaume ,Gerard Dreyfus et.al[2019] present a cognitive brain computer interface dependent on a persistent execution task for the checking of varieties of visual supported consideration, for example self-directed maintenance of cognitive concentration in non-stimulating conditions while potentially disregarding distractors and keeping away from mind wandering. Generalization execution assess for pairwise arrangement of assignment trouble utilizing these highlights reached75% for 5 s ages, and 85% for 30 s ages.

These Aurelien Appriou , Andrzej Cichocki et.al authors in this paper investigates such machine learning algorithms, proposes new variations of them, and benchmarks them with traditional strategies to appraise both mental remaining burden and full of feeling states (Valence/Arousal) from EEG signals. They study these methodologies with both subject-explicit and subject-autonomous adjustment, to go towards alignment free frameworks. Their outcomes proposed that a CNN got the most noteworthy mean exactness, albeit not fundamentally in this way, in the two conditions for the psychological remaining task at hand study, trailed by RGCs. Nonetheless, this equivalent CNN failed to meet expectations in the two conditions for the feeling informational index, an informational collection with little preparing information. Despite what might be expected, RGCs demonstrated to have the most elevated mean precision with the Filter Bank Tangent Space classifier (FBTSC) they presented in this paper. Their outcomes subsequently added to improve the dependability of intellectual and emotional states characterization from EEG. They additionally give rules about when to utilize which AI calculation.

V.CONCLUSION

Emotion is one of human being's most important characteristics. It is a combination of human thinking, feelings and actions. This is important multidisciplinary study topic in various domains such as psychology, neuroscience, computer science, cognitive science and artificial intelligence. In this study contains the work on emotions like valence and arousal has done by the various author. There has been increasing interest in utilizing EEG signals to determine the cognitive state of students as they engaged in various learning activities. Detecting cognitive skill is a crucial step towards adaptive learning. This review contains the assessment of cognitive states during learning activities. In particular, the researchers has done mostly work on cognitive states such as attention , workload , inattention , memory and engagement in the field of medical ,engineering ,programing and mathematics with the help of BCI based EEG. And also this paper analyzed the various neuroimaging techniques available for Brain signal acquisition used for analyzing the Human Emotions among these most of the authors has preferred noninvasive EEG techniques for analyzing the Emotions. BCI systems based Electroencephalogram is very crucial component in Human Emotion Estimation also this study useful to obtaining an accurate view of learner’s mental state at the time of learning activities using BCI based EEG which helps to students for enhancing their cognitive skills as well as learning.

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