ISSN: 2093-5374 / E-ISSN: 2093-5382

IoT-Based Monitoring of Students' Brain Activity Using an Ensemble Method in E-Learning Classes

I. Rufia Thaseen[1*], and Dr.S. Shahar Banu[2]

[1*]Department of Computer Applications, BS Abdur Rahman Crescent Institute of Science and Technology, Chennai, Tamil Nadu, India. rufia.thaseen93@gmail.com, https://orcid.org/0009-0008-2187-5726

[2]Associate Professor, Department of Computer Applications, BS Abdur Rahman Crescent Institute of Science and Technology, Chennai, Tamil Nadu, India. shahar@crescent.education, https://orcid.org/0009-0005-6258-8940

Received: February 02, 2024; Revised: March 24, 2024; Accepted: May 02, 2025; Published: June 30, 2025

Abstract

Perceiving the attentiveness of students in online classes has become critical after the pandemic situation due to a larger number of students involved in a single class, which becomes complex in improving the education quality in online mode. However, each student's participation has a different degree of proficiency, but the main goal of the online education is to improve their standard of teaching methodology. Hence, this research study introduced the Internet of Things (IoT) based online platform and evaluated the engagement level of students through online lessons. These technologies empower devices physically embedded for connecting to the internet are integrated extensively into human action by supporting several activities. In real time, Peripheral neurophysiological signals are less responsive to changes in affective states than the Electroencephalogram (EEG) signal. Thus, the student's brain activity during online classes has been monitored through various frequencies of the brain obtained from Electroencephalography (EEG) devices. Moreover, the Machine Learning (ML) method with lazy predict classification library through an ensemble predictive system by soft voting concept for assisting the staff to identify student attitude in listening the online classes and justify the student's potential in their academic. Thus, the proposed ensemble ML prediction system with IoT-based EEG has helped in determining the exact prediction of students' brain activity for providing them a set of interesting classes from the online teaching staff.

Keywords: E-Learning, Student Performance, Student Brain Activities, Electroencephalography (EEG), Weighted Average, Internet of Things (IoT).

1 Introduction

The major influence of student performance in factor analysis is one of the key concerns for educational institutions. Each institution makes an effort to lower student failure rates. Educational Data Mining (EDM) is the most widely used method to assess and forecast students' performance (de Andrade et al., 2021). To enhance students' learning results, EDM focuses on creating strategies for handling the various types of data that educational systems generate (Romero & Ventura, 2020). Data mining, machine

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 16, number: 2 (June), pp. 1-15. DOI: *10.58346/JOWUA.2025.I2.001*

*Corresponding author: Department of Computer Applications, BS Abdur Rahman Crescent Institute of Science and Technology, Chennai, Tamil Nadu, India.

learning, and statistical methods are developed and modified by EDM. The main goal of EDM is to obtain information from educational data to make educational decisions. Early academic performance predictions can be made through EDM. They could be used to enhance the study of how children learn while taking into consideration the way they interact with their environment. To enable people to access and learn the subjects from anywhere, as well as at any time. The e-learning makes use of digital technology, mostly the internet, including smartphones and computers (Tudor Car et al., 2018). As a result, e-learning facilitated the development of a variety of skills and important knowledge among users (teachers and students) in educational institutions (Alsharifi,2023). Many educational institutions around the world moved from direct instruction to online as well as distance learning during the time of COVID-19 pandemic. A set of electronic instructional resources and the option to share them in a variety of formats, including PowerPoint slides, audio files, Word documents, PDF format, videos, and photos, were provided by the e-learning system to aid in the educational process (Racovita-Szilagyi et al., 2018). Additionally, it facilitates, enhances, and improves teacher-student interaction (Marunevich et al., 2021). In addition to designing quizzes, examinations, and assignments, teachers can upload a variety of materials for a particular course and pose specialized discussion topics.

Cooperation and student participation are essential for an effective learning environment. Increased involvement and understanding of the student's context are possible with the help of the IoT. Additionally, the behavior of students is a reliable predictor of mental abilities. Predictor is utilized for determining students' participation, and evaluating student focus is a crucial part of educational evaluation. The majority of research on e-learning platforms is focused on teaching-learning approaches and is restricted to improving teaching methodologies. The role of IoT cannot be ignored in contemporary education or e-learning systems (Vijayalakshmi & Jayasimman,2018), (Gao, 2024), (Hajjaji & M'barki, 2018). There are several solutions for enhancing effectiveness, speed, and quality in the daily activities of teachers and students that have been made possible by the IoT in education. An educational establishment is capable of carrying out a wide range of duties, including monitoring necessary supplies, monitoring pupils, creating data and resource access, and creating a secure learning environment. When learning is performed through IoT, productivity has increased gradually (Eiriemiokhale & James, 2023). According to their findings, it is impossible to ignore the IoT's impact on the present-day educational system. E-learning and digital learning have become essential for various reasons. The freedom and opportunity to learn at anytime, anywhere and IoT in e-Learning is beneficial, essential, and necessary (Zahedi & Dehghan, 2019; Prasanth & Rajesh, 2016). The procedures and goals for each module were outlined. The IoT can provide a flexible platform and promote e-learning, they concluded. Face VR paradigm based on virtual reality has been presented (Thies et al., 2018). Personalized experiences for learning, where educational materials and methodologies are modified to match the needs of the student, enhancing engagement and comprehension, are now available thanks to the IoTs. Learning may be made more pleasant and conducive with the help of IoT-enabled smart classrooms that have better lighting, temperature control, and air quality. With instant feedback on their performance, students can now improve faster by learning from their mistakes. Teachers are now better able to come up with data-driven decisions that benefit individual students as well as educational institutions overall because of the insights into student performance offered by IoT-generated data (Ghashim & Arshad, 2023; Mauryan & Sakthi, 2020). Examined several security dangers and weaknesses and made numerous suggestions for potential remedies. In addition, they offered a comprehensive security model procedure and principles which influence the architecture of IoT (Bansal & Khan, 2018).

Providing access to the students in a wide variety of both explicit as well as implicit understanding nodes when allowing the students freely to select as well as arrange the nodes in any case that individual student is fit for developing their network of personal knowledge has become the foundation of the knowledge-pull approach to learn as well as teach. In this day and age, traditional pedagogical methods are ineffective. When IoT is implemented in the classroom, there will surely be more pedagogical problems. As a result, researchers and academics are inspired to develop innovative educational strategies to improve the learning process for students. The smart educational environment, which is opposite to the conventional educational environment, provides learners with constant access to resources and learning systems, making it possible to learn wherever people want to learn. Even technology is available in these situations to choose the best time and place for a student to learn. The Smart Learning Platform is more effective and engaging. A range of hardware and software solutions can be used to implement such learning environments. Examples of hardware include a tablet, smartphone, an e-bag, an interactive whiteboard, smart tables provided in the classroom, etc. Software components such as learning tools and systems, communication and social networking, inclusive of blog resources, online resources, virtualization technologies, and analytical tools, have suggested a smart educational model. The majority of e-learning studies are focused on teaching-learning techniques and are only concerned with improving teaching practices. Each student has a unique method of approaching their education. There are few research studies on the topic of understanding students' learning styles. This study emphasizes the value of grading students by their preferred learning styles, especially aural, kinaesthetic and visual. Additionally, there hasn't been much focus on the usage of IoT as well as brain signal techniques in understanding students' learning approaches.

The proposed framework will use IoT devices and machine learning technologies to determine all students' learning patterns. Based on that, assessments will be given, and pupils will be evaluated properly. The use of an IoT-based architecture and an integrated sensor layer in an e-learning platform to gather behavioral, environmental, and physical data. This information can be used to improve the platform and provide features like context awareness. To conduct intelligent solutions that meet the needs of the user, teachers can use cognitive modules. As a result, in the data-fueled academic era, this research work concentrates on the IoT-entity context, which shows the design components of architecture and the corresponding links associated to gathering and tracking data from connected equipment such as cameras, tablets, barcoding systems, RFID sensors, smartphones, EEG devices, and handheld gadgets. As a result, the design is integrated with the ensemble method, which aids in enhancing the ensemble forecasting system's ability to precisely identify fundamental epilepsy and student brain activity. This is done automatically by recognizing the EEG signals of the students, with the help of teachers and staff. The structure of this paper is as follows: session 2 illustrates the various approaches to improve the skill set of e-learning students and the benefits of ML in e-learning for predicting student activity in the online learning system. Session 3 illustrates the "soft voting" based on various ensemble methods for predicting the skills of students using an EEG device with IoT IoT-enabled e-learning method. Session 4 illustrates the performance evaluation of the stacking classifier and the voting classifier as an ensemble technique with another existing ML method. Session 5 illustrates the conclusion for selecting the stacking ensemble method to predict student attentiveness using EEG-based IoT monitoring through their brain activity status.

2 Literature Review

Online education is becoming more and more popular with experts who are interested in developing their professions, students are learning recent skills but keeping their current employment status, and students want to receive training or get ready for certification examinations. As more students engage in online courses, institutes are finding it more and harder to carefully monitor and evaluate their courses

(Balakrishna et al., 2021). For permitting the students to use the network as a platform, educational institutions are heavily investing in online instruction and learning due to a lack of mentors and tutors. A global audience of networked learners is accessible over the Internet, and they may all use high bandwidth applications such as simulations, video conferencing, and animations (Abdellatif et al., 2021). Along with online courses, the website provides a collaborative setting for exchanging resources with others. When students interact with online learning environments like MOOCs, sensors are used as part of the IoT to capture their data. This data has been sent to the central database system so it can be examined. Using IoT to enhance online teaching and learning is the aim of this research study. To filter, arrange, combine, and evaluate data to provide reports for different management levels, several Data Mining (DM) techniques will be implemented within the central database systems (Muteba et al., 2020).

The term "e-learning" describes the integration of technology into the study and practice of education. To increase their knowledge without using conventional teaching methods, students might use virtual classrooms offered by e-learning. The letter "e" has come to represent the information technology era in which it currently lives as an outcome of the rapid expansion of technological development in communication and information in today's environment (Su et al., 2022). Electrical parts are frequently denoted by the letter "e". The prefix "e" is growing in popularity across all industries, as seen by the creation of terms, namely "e-learning," "e-business," "e-health," "e-government," etc. The importance of e-learning in the field of education is growing as a result of networking, globalization and the peak of information technology (Anthi et al., 2021). Globalization, IT and networking are the driving forces of the modern world. Social media in e-learning is crucial to improve the learner experience. Social media marketing has been increasingly popular in recent years as a means of promoting educational materials, training programmes, study aids, and enrollment in new courses. The social media platforms Google Plus, YouTube, Twitter, Facebook, and LinkedIn are the most often utilized for marketing. The list of social media sites in India is mentioned in the table below. IoT is a commonly used technology that enables online collaboration and communication. It expands in scope and depth as it advances, having an impact on many facets of our lives, including educational opportunities (Rahman et al., 2020). Education e-learning will progress with the IoT. By leveraging the capabilities of the IoT and EEG, we can create a smart learning environment that encourages improved learning and increased retention rates. Better people will be produced as a result of this educational advancement in terms of knowledge and skills. This essay examines the applications, significance, and need for the IoTs with an emphasis on improving the caliber of student e-learning (Kumar & Al-Besher, 2022).

The IoT makes it possible to expand learning settings by fusing real and virtual objects without hindering the learning process. As a digital technique, traditional e-learning can provide students with a wide range of virtual environments, however, it also comes with significant drawbacks, which are mentioned below (Kebande et al., 2020). The geographical location, direct interaction among objects, as well as successful collaboration among virtual and actual agents, are the main restrictions in e-learning environments. One possible remedy for the challenges mentioned above is the use of intelligent things in the environment of learning environment. Commonly acknowledged as a highly significant source of intelligent agents in e-learning, the IoT is a growing field. Intelligence and object interaction are two crucial components that the IoT may incorporate into conventional e-learning (Esmail Karar et al., 2021). IoT has the capability of creating a broad platform that students as well as instructors can use in accessing a variety and equipment for distance learning. There could be a wide variety of collaboration circumstances created as a result of virtual and real commodities with a significant range of interaction.

Research Gap

Human emotions can be recognized by speech, body language, gestures or posture, and physiological indicators, whereas these three are ineffective because people occasionally conceal their actual feelings, either knowingly or unknowingly said to be social masking. The general objective of emotion recognition can be accurately achieved using physiological signals. In real time, Peripheral neurophysiological signals are less responsive to changes in affective states than the Electroencephalogram (EEG) signal. However, EEG signals can disclose significant aspects of emotional experiences. Therefore, there are several EEG-based BCI emotion recognition methods have been developed recently. In addition, quick developments in ML and deep learning have made it possible for computers to comprehend, identify, and evaluate emotions (Houssein et al., 2022). This paper presents an overview of the state of the art in emotion recognition techniques concerning multi-channel EEG signal-based BCIs. Thus, it presents a summary of the datasets and techniques utilized to evoke different emotional states.

3 Research Methodology

Students are expected to finish their assignments online because educational institutions have to close due to safety procedures during the pandemic outbreak. Pupils can comprehend the subjects clearly by raising the bar for education. The key factor contributing to the decline in educational quality is students' inability to understand and learn the material. Administrators can use the "IoT" to improve education standards in this emerging mobile digital world. The student's preferred technique of learning is the key to comprehending and appreciating their power. For the successive school, students must be able to use their distinctive learning style effectively. Students' chosen learning styles are considered while assigning exercises, tutorials, and assignments to ensure that they can understand the topic well and make progress. Even if it may be challenging, it is important to determine each student's ideal learning method.

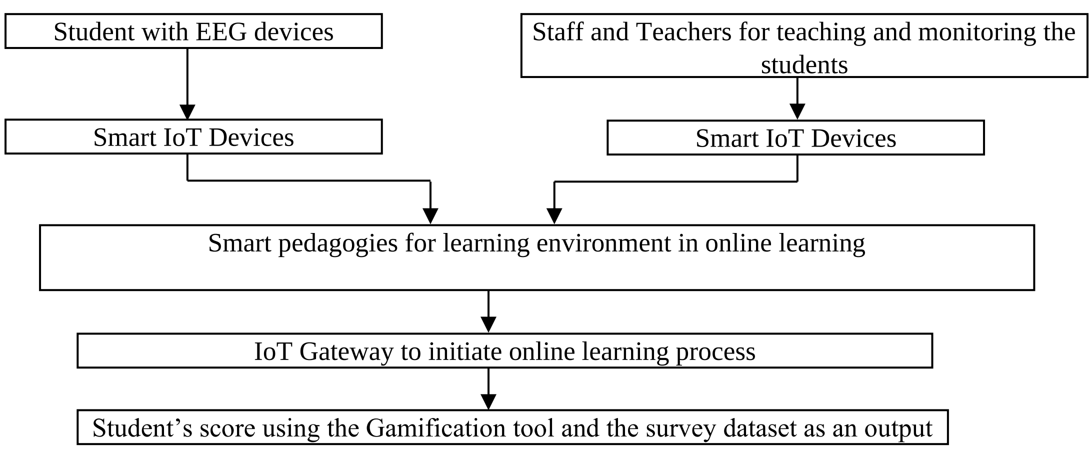


Figure 1: Architecture for IoT-Based EEG in Online Learning Process

Moreover, the experimental research will leverage pervasive linked technology and the IoT. It enhances its predictive analytics capabilities using recent academic data. Teachers can use sophisticated tools to manage and optimize educational choices among networked resources by combining intelligence and insights. The IoT makes it possible for educational institutions to collect as well as monitor data from linked devices, including barcode readers, tablets, smartphones, RFID sensors, cameras, EEG equipment, and portable electronics. These academic years have seen the usage of IoT with entity-based e-learning, smart learning environments, and IoT gadgets for e-learning, as shown in Figure 1.

EEG Device Acquisition

An EEG records the nervous system's brain impulses. The electrodes on the device measure brain activity when placed on the scalp of a subject. The electrodes capture the brain wave patterns, and the EEG gadget transfers the data to a computer or cloud server. The EEG device used in the experiment is the Emotiv Epoc X 14 channel headset was utilized to record EEG data with dry electrodes, which are transportable and convenient. There are EEG sensors in eight positions spread over the scalp of this headset, and there are also accelerometers, which are three-dimensional acceleration sensors. Based on the earlier studies' working procedures, the following electrodes are placed namely two central, frontal, parietal, and occipital electrodes. C4, C3, O1, FP2, FP1, P8, P7, and O2. Table 1 below lists the range of brain frequency bands. These signals have been recorded, as well as communicating data sent to the system using the data gathering, processing, and design programme Open Vibe. The data were gathered at a sample rate of 256 Hz and filtered using a 4th-order Butterworth bandpass filter with a passband of 0.1-100 Hz. The EEG device used in the experiment is the Emotiv EPOC X 14 channel head set. Every EEG recording was cleaned up using the Artefact Subspace Reconstruction (ASR) method, which acts as a potent as well as successful signal cleansing method which has recovered artefacts to within double the standard error of a signal cleansing section.

Table 1: Status of the Brain using the Brain Frequency Range

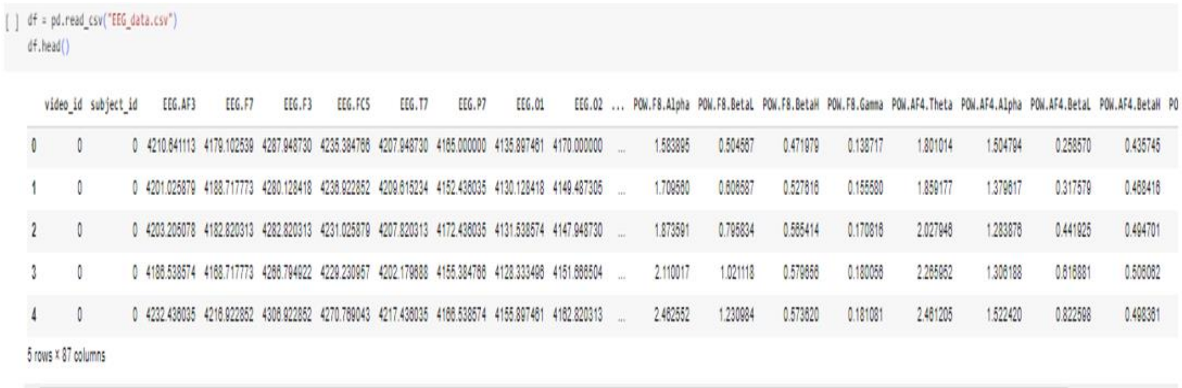
Brain frequency type	**Bandwidth Range in Hz**	**Purpose and status of the brain**
Delta	0.50 to 2.75	Deeply meditating and sleeping
Alpha	7.50 to 11.75	Relaxing or thinking normally
Beta	13.00 to 29.75	Focusing or thinking intently
Gamma	31.00 to 49.75	Conscious and perceptual thinking
Theta	3.5 to 6.5	Sleeping or meditating

Smart IoT Devices

User events can be responded to by these connected "objects." PCs, IoT sensor devices, smartphones, and Tablets are a few examples of possible gadgets. Any object that a student owns and is connected to the system can be considered a smart IoT device.

Dataset Collection

A conventional grading system was used to assess the students' work, and at the same time, an internet setting allowed students to share posts, get feedback, and categorize projects based on their perceptions. Several students are invited with varying levels of education to monitor online lectures as well as record their EEG data and the brain waves during the lecture. This research conducted many online video classes and identified the students' attitude by their frequency range and understanding of their knowledge base, as well as picked several videos. These several videos assist in understanding that students aren't able to understand as well, and certain students are not listening to the classes. Thus. It can be analysed through recorded data of their EEG brain waves, as well as accumulating the binary variable that specifies whether the student can understand the lecture or not ('1' represents understanding the lecture and '0' represents not understanding the lecture). There are nearly 24 students involved, and their sample with 68,831 records from their hourly class for nearly 6 months of monitoring. All the recordings and appended are considered in a single dataset (EEG data.csv). The time online represents their presence and involvement in an online class. Similarly, the student's interest in listening to the class can be monitored through EEG, as shown in Figure 2.



```
[ ] df = pd.read_csv("EEG_data.csv")
    df.head()
```

	video_id	subject_id	EEG.AF3	EEG.F7	EEG.F3	EEG.FC5	EEG.T7	EEG.P7	EEG.O1	EEG.O2	...	POW.F8.Alpha	POW.F8.BetaL	POW.F8.BetaH	POW.F8.Gamma	POW.AF4.Theta	POW.AF4.Alpha	POW.AF4.BetaL	POW.AF4.BetaH
0	0	0	4210.841113	4179.102539	4287.948730	4235.384766	4207.948730	4165.000000	4135.897461	4170.000000	...	1.583895	0.504587	0.471979	0.138717	1.801014	1.504794	0.258570	0.435745
1	0	0	4201.025879	4188.717773	4280.128418	4238.922852	4209.615234	4152.436035	4130.128418	4149.487305	...	1.709560	0.606587	0.527816	0.155580	1.859177	1.379617	0.317579	0.468416
2	0	0	4203.205078	4182.820313	4282.820313	4231.025879	4207.820313	4172.436035	4131.538574	4147.948730	...	1.873591	0.795834	0.565414	0.170816	2.027948	1.283878	0.441925	0.494701
3	0	0	4186.538574	4168.717773	4266.794922	4229.230957	4202.179688	4155.384766	4128.333496	4151.666504	...	2.110017	1.021118	0.579656	0.180056	2.265952	1.306188	0.616881	0.506062
4	0	0	4232.436035	4216.922852	4306.922852	4270.769043	4217.436035	4166.538574	4155.897461	4162.820313	...	2.462552	1.230984	0.573620	0.181081	2.461205	1.522420	0.822598	0.498361

5 rows × 87 columns

Figure 2: IoT with EEG Signal-Based Skill Analyzed Students Dataset

Initially, data preparation is performed with missing imputation, and the robust scalar is utilized to scale the distinct variable value. All the variables are in the form of integer data type, the dataset is prepared for modelling once the data is split into 80% of the population as the train dataset and 20% of the population as the test dataset. The traditional ML classification method is introduced, and ensemble learning is implemented to obtain better accuracy in identifying students' skills and the student's reaction posts. Moreover, the EEG signal has been utilized to identify the individual student's brain status, which assists the staff and teachers in monitoring the student's brain activity. Hence, the teacher and staff can provide an alternate mode of teaching, like conducting choose-the-answer-based questions as a quiz in between classes, to the students attending the respective subjects. Thus, the ensemble model assists in improving the accuracy of the student's brain attitude is discussed.

Working of Stacking Ensemble Method (SEM)

A sort of ensemble learning called stacking that makes use of numerous regression or classification models by providing predictions which is more accurate. This method makes the final prediction by feeding the output of multiple base models into a meta-model. After being trained on the input data, the base models produce their predictions. The meta-model then uses these combined predictions as inputs and learns from them to produce a final prediction. By stacking multiple models, one can use their strengths to produce a prediction that is more accurate and reliable than it would be from any one model working alone. Based on the proposed ensemble learning model, this research focuses on stacking patterns with 'n' number of classifiers selected for ensemble classification, as shown in Figure 3.

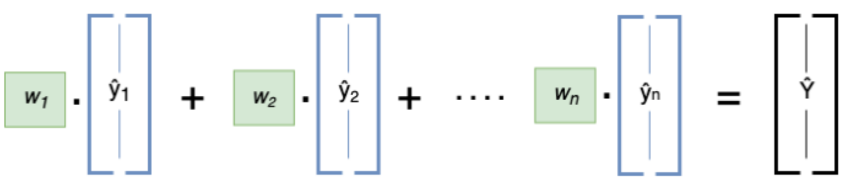


Figure 3: Basic Principle of SEM

In this experimental research, a lazy predictive classifier library is implemented for modeling to predict the student's online learning detection through EEG-based IoT technology presented in **Table 2**.

The top three classifiers have been considered in detecting the student understanding, as well as the brain activity of the behavior, by the accuracy metrics in Figure 4. The three classifier are denoted as LP-CF1, LP-CF2 and LP-CF3 whereas the

- LP-CF1 - XGB classifier
- LP-CF2 – Extra Tree classifier (ETC)
- LP-CF3 - Light Gradient Boosting Machine (LGBM) classifier

However, the ensemble using staking as weight-based has been concentrated in minimizing the correlation between 'n' estimators through SEM, and it classifies the features by random sampling instead of the entire feature set. Hence, the mechanism of SEM is measured through weights to specific features by the significance of the target variable, as well as by achieving the final result.

Table 2: Lazy Predict Classifier Sorted as per Accuracy

Classification Model	**Accuracy**	**Balanced Accuracy**	**AUC**	**F1 Score**	**Time Taken**
XGB Classifier	0.97	0.97	0.97	0.97	0.95
Extra Tree Classifier	0.97	0.97	0.97	0.97	4.08
LGBM Classifier	0.97	0.97	0.97	0.97	0.82
Random Forest Classifier	0.96	0.96	0.96	0.96	10.05
Bagging Classifier	0.95	0.95	0.95	0.95	4.70
K Neighbors Classifier	0.94	0.93	0.93	0.93	1.18
Decision Tree Classifier	0.92	0.92	0.92	0.92	0.64
Label Propagation	0.92	0.92	0.92	0.92	23.17
Label Spreading	0.92	0.92	0.92	0.92	45.02
Extra Tree Classifier	0.87	0.87	0.87	0.87	0.09
Ada boost Classifier	0.85	0.85	0.85	0.85	7.78
SVC	0.83	0.83	0.83	0.82	23.11

The technique of ensemble learning through the stacking mechanism of various classifier ML models. The traditional algorithms are capable of an entire training data set in which the Meta model has learned by eventually finding features using the complete base-level model. Moreover, this experimental research has included bagging as well as boosting techniques, maintaining bias as well as variance, which assists in understanding the stacks that have increased the predicting accuracy of SEM. Hence, the alternative to a voting-based classifier is a stacking-based weighted average blending level, which helps to learn the best aggregation of individual outcomes. Thus, the proposed SEM is used to identify the specific weighted features with each traditional ML algorithm, resulting in complexity for regression. The SEM has been illustrated in equation 3.1.

$$SEM_{CF} = w_1 * P_1 + w_2 * P_2 + w_3 * P_3 + \cdots + w_n * P_n \quad (3.1)$$

Where:

SEM_{CF} = Weighted average of the Meta classifier model

P_n = Prediction of the n^{th} traditional ML classifier model

w_n = Weight of the definite feature of the nth traditional ML classifier model

As a result, the SEM-assisted LR accurately predicted students' satisfaction with attending online learning. The SEM-based model is illustrated briefly for predicting students' attentiveness and learning in online learning.

SEM Algorithm

Input: Student EEG data collected from IoT devices, x as dataset and y as label

Output: Classifying classes concerning attentiveness in class or not

Step 1 – Calculating point-biserial for each continuous and discrete column using pointbiserialr ().

Step 2 – train_ test_ split () for splitting the dataset into a train and a test dataset. Standard Scaler () for data preprocessing.

Step 3 – Analyse LP-CF_1. Fit (x, y), LP-CF_3. Fit (x, y) and LP-CF_3. Fit (x, y)

Step 4 – Generate Meta level prediction LP-CF_1.predict_proba(x_val)', LP-CF_2.predict_proba (x_ val)' and LP-CF_3.predict_proba (x_ val)'

Step 5 – concatenate using np. column_ stack ()

Step 6 – ensemble = meta. Fit (np. column_ stack (), y_ val)

Step 7 – fin_ ensemble= meta. Predict (np.column_stack (), y_val)

Step 8 – return fin_ ensemble

This fin_ ensemble determines with high accuracy in detecting the classes effectively. To achieve an improved outcome when predicting a student's behavior with the EEG signal representation of using IoT as "Understood lecture" or "Not understood lecture". By analyzing records, the SEM has generated high accuracy through choosing the exact correlated features identified from the various classifiers for the brain activity of students through the frequency ranges obtained.

4 Experimental Result

Based on the experimental research, the e-learning dataset involved 80 instances after wrangling data, in which 80% dataset was measured as the sample training dataset, and the remaining 20% was considered a random sample and is considered to be the testing dataset. However, the better prediction is determined by the top LP-CF models as an individual classifier. The prediction of three individual classifiers recognised and the parameter value of the confusion matrix for XGB classifier, ETC and LGBM classifiers compared with the proposed SEM with XGB classifier is illustrated in Table 3. Therefore, the confusion matrix of SEM with XGB classifier is shown in Figure 5and Jupiter notebook is used for carrying out the implementation performance. The obtained result for evaluating the performance in SEM with the XGB classifier model has been compared with the confusion matrix parameter values of existing traditional classifier predictions.

Table 3: Confusion Matrix Value in WAEM with other Existing Classifiers

ML classifier Method	True Positive (TP)	True Negative (TN)	False Negative (FN)	False Positive (FP)
XGB Classifier	3482	3557	119	73
ETC	3419	3580	182	50
LGBM Classifier	3434	3550	167	80
Soft Voting Ensemble	3471	3571	130	59
SEM with XGB Classifier	3496	3548	105	82

The performance of the confusion matrix is used to evaluate the model's effectiveness in performance of predicting students' brain activity effectively. The accuracy metric is estimated by the correct prediction count from the overall students involved in the online observation.

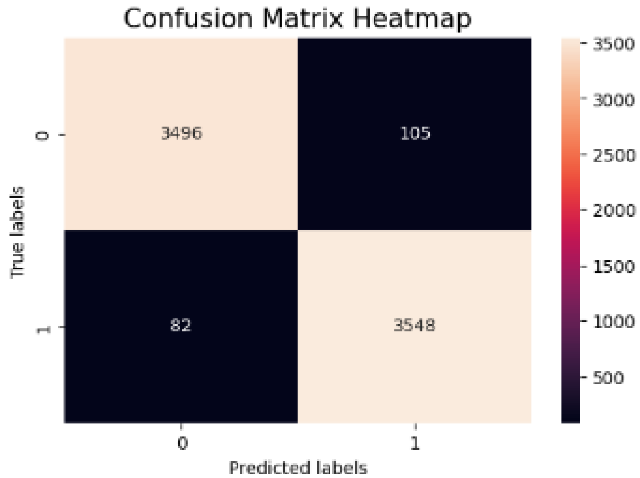


Figure 4: Confusion Matrix Heat Map for SEM with XGB Classifier

Accuracy (Acc)

The Acc is defined as the amount of exact prediction of student brain activity from the complete student sample in the e-learning dataset.

$$\mathrm{Acc} = \frac{TN + TP}{TN + TP + FN + FP}$$

Precision

Precision is a measure of correctness presented for positive prediction of student brain activity that performs better, which illustrates positive prediction of e-learning students as a result of actual positive results.

$$Precision = \frac{TP}{FP + TP}$$

Recall

It is defined as TP is predicted from all positive-based students present in the e-learning student dataset, which is also named as true positive rate.

$$Recall = \frac{TP}{TP + FN}$$

Table 4: Confusion Matrix Metrics Value for Distinct ML Methods

ML classification methods	**Accuracy**	**Recall**	**Precision**	**Sensitivity**	**Specificity**
XGB Classifier	0.9734	0.9795	0.9670	0.9795	0.9676
ETC	0.9679	0.9856	0.9495	0.9856	0.9516
LGBM Classifier	0.9658	0.9772	0.9536	0.9772	0.9551
Soft Voting Ensemble	0.9739	0.9833	0.9639	0.9833	0.9649
SEM with XGB Classifier	0.9741	0.9771	0.9708	0.9771	0.9713

Moreover, the sensitivity and specificity represent TP rates and FP rates, respectively; the suggested WAEM performs with high accuracy.

Table 4 illustrates the SEM with XGB Classifier performing the high prediction of student brain performance, as well as reaction datasets. Generally, the SEM with XGB Classifier accuracy is relatively higher than the soft voting ensemble model and traditional ETC, XGB classifier and LGBM classifier methods. Moreover, the SEM has generated high accuracy for predicting student skill set and creativity through EEG signal, and their performances are analyzed by the teacher and staff. Hence, each model with the SEM with the XGB Classifier model is analyzed are shown in Figure 5.

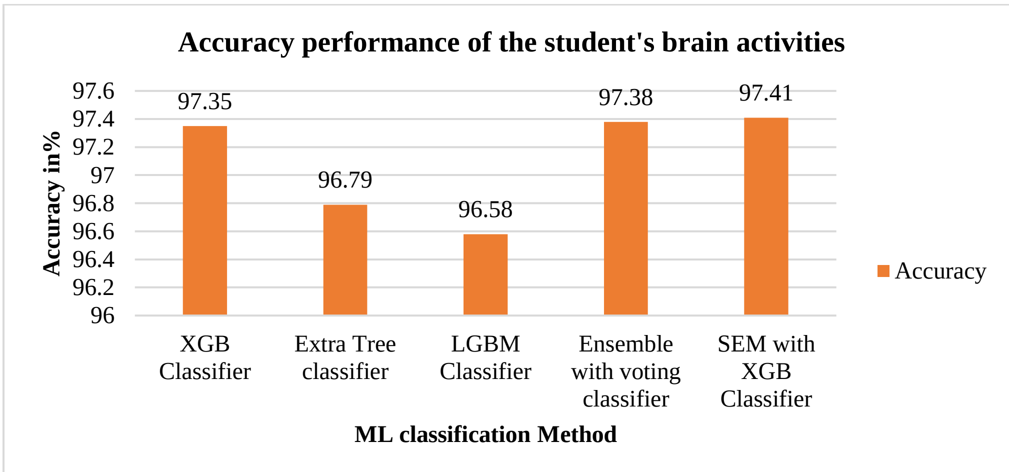


Figure 5: Accuracy Performance Comparison of Online Learning Students

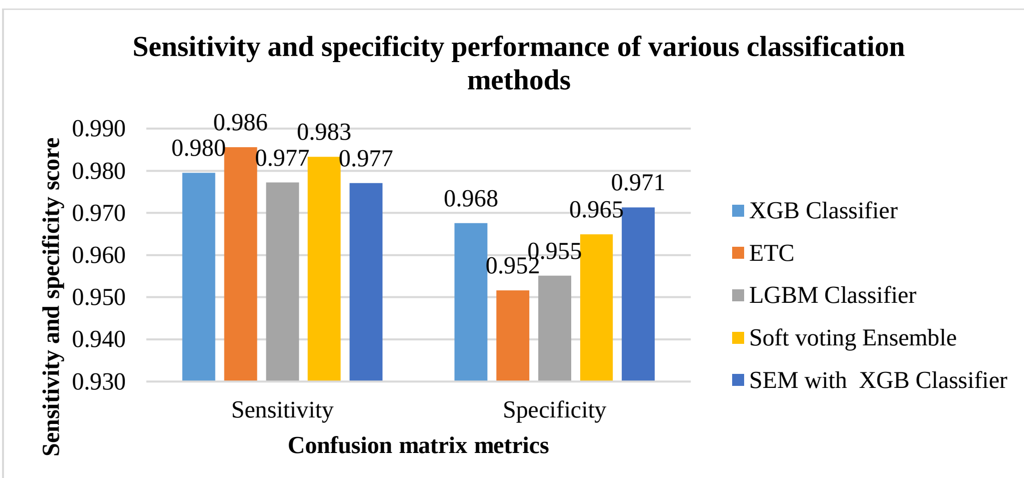


Figure 6: Sensitivity and Specificity Performance Comparison of Online Learning Students

In the case of precision, the measurement ratio of positive prediction and total positive prediction in which the proposed SEM with XGB Classifier is 0.977, but the sensitivity score is 0.986 which is higher than the proposed SEM with XGB Classifier, soft voting ensemble, and top three lazy predict model is shown in Figure 6. The sensitivity or recall is higher in the ETC method than soft voting ensemble and the top three lazy predict models, whereas the positive prediction of student skill status is set in online learning when compared with other existing methods. Similarly, the specificity is evaluated in which proposed SEM with XGB Classifier is 0.971 which indicating better detection, of not precisely understand. Thus, the proposed model assists in identifying the student who is not attentive to the class more perfectly.

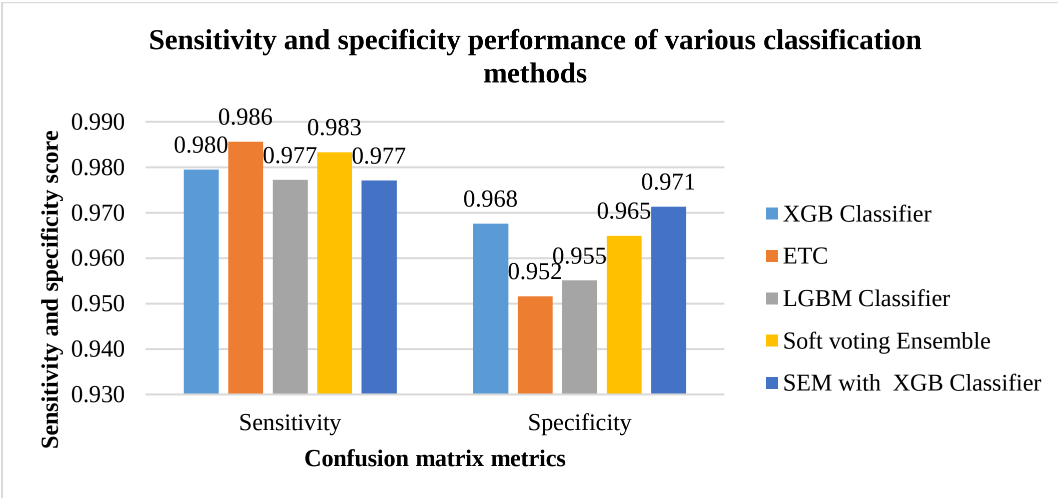


Figure 7: Performance Comparison of Online Learning Students by Sensitivity and Specificity

Figure 7 illustrates the Area Under the ROC Curve (AUC) for the top three lazy prediction classification methods and two different ensemble models, such as a voting classifier and SEM with an XGB classifier. The AUC performance of the voting ensemble model is 0.9969, followed by SEM with XGB classifier as 0.9966, which indicates that the ensemble model has better True Positive Rate (TPR) and False Positive Rate (FPR) of the student's brain activity detection in figure 8.

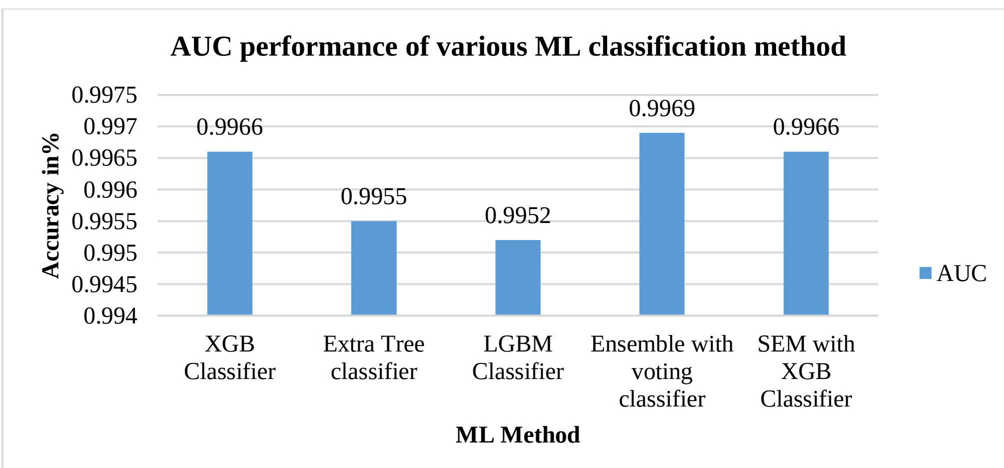


Figure 8: Performance Comparison of Online Learning Students by AUC

5 Conclusion

This research mainly concentrated on outlining the huge innovations that the IoT will bring to every sector of the economy. Online learning will advance in the field of education thanks to the IoT. By making use of the IoT and EEG, it has created an environment of smart learning which influences better learning as well as increased retention rates. However, the advancement of education will help in generating individuals who are better based on their skills as well as knowledge. Hence, this essay examines the necessity, value, and applications of the IoT with a definite emphasis on how to improve the standard of online instruction for students. In addition, it recommended IoT-based smart learning as the most effective e-learning method for predicting student attentiveness. The usage of the SEM approach for aggregating the top three lazy prediction classification methods outperforms the high prediction with higher accuracy than soft voting ensemble and traditional ML methods. This experimental research on IoT with EEG signal-based student skill set is a measure for SEM classification accuracy for each student to assist in improving their academic skill in an online learning platform.

References

[1] Abdellatif, A. A., Mhaisen, N., Mohamed, A., Erbad, A., Guizani, M., Dawy, Z., & Nasreddine, W. (2022). Communication-efficient hierarchical federated learning for IoT heterogeneous systems with imbalanced data. *Future Generation Computer Systems*, *128*, 406-419. https://doi.org/10.1016/j.future.2021.10.016

[2] Alsharifi, A. K. H. (2023). Total Quality Management Strategies and their Impact on Digital Transformation Processes in Educational Institutions. An Exploratory, Analytical Study of a Sample of Teachers in Iraqi Universities. *International Academic Journal of Organizational Behavior and Human Resource Management*, *10*(1), 1-16. https://doi.org/10.9756/IAJOBHRM/V10I1/IAJOBHRM1001

[3] Anthi, E., Williams, L., Javed, A., & Burnap, P. (2021). Hardening machine learning denial of service (DoS) defences against adversarial attacks in IoT smart home networks. *computers & security*, *108*, 102352. https://doi.org/10.1016/j.cose.2021.102352

[4] Balakrishna, K., Mohammed, F., Ullas, C. R., Hema, C. M., & Sonakshi, S. K. (2021). Application of IOT and machine learning in crop protection against animal intrusion. *Global Transitions Proceedings*, *2*(2), 169-174. https://doi.org/10.1016/j.gltp.2021.08.061

[5] Bansal, H., & Khan, R. (2018). A review paper on human computer interaction. *International Journal of Advanced Research in Computer Science and Software Engineering*, *8*(4), 53.

[6] de Andrade, T. L., Rigo, S. J., & Barbosa, J. L. V. (2021). Active methodology, educational data mining and learning analytics: A systematic mapping study. *Informatics in Education*, *20*(2), 171.

[7] Eiriemiokhale, K., & James, J. B. (2023). Application of the Internet of Things for quality service delivery in Nigerian university libraries. *Indian Journal of Information Sources and Services*, *13*(1), 17-25. https://doi.org/10.51983/ijiss-2023.13.1.3463

[8] Gao, Q. (2024). Decision support systems for lifelong learning: Leveraging information systems to enhance learning quality in higher education. *J. Internet Serv. Inf. Secur*, *14*(4), 121-143. https://orcid.org/0009-0000-5685-6164

[9] Ghashim, I. A., & Arshad, M. (2023). Internet of things (IoT)-based teaching and learning: modern trends and open challenges. *Sustainability*, *15*(21), 15656. https://doi.org/10.3390/su152115656

[10] Hajjaji, S. E., & M'barki, M. A. (2018). The Higher Education Quality Concept: Comparative Analysis between the Universities of Morocco and Spain. *International Academic Journal of Innovative Research*, *5*(1), 1–8. https://doi.org/10.9756/IAJIR/V5I1/1810001

[11] Houssein, E. H., Hammad, A., & Ali, A. A. (2022). Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review. *Neural Computing and Applications*, *34*(15), 12527-12557. https://doi.org/10.1007/s00521-022-07292-4

[12] Karar, M. E., Abdel-Aty, A. H., Algarni, F., Hassan, M. F., Abdou, M. A., & Reyad, O. (2022). Smart IoT-based system for detecting RPW larvae in date palms using mixed depthwise convolutional networks. *Alexandria Engineering Journal*, *61*(7), 5309-5319. https://doi.org/10.1016/j.aej.2021.10.050

[13] Kebande, V. R., Ikuesan, R. A., Karie, N. M., Alawadi, S., Choo, K. K. R., & Al-Dhaqm, A. (2020). Quantifying the need for supervised machine learning in conducting live forensic analysis of emergent configurations (ECO) in IoT environments. *Forensic Science International: Reports*, *2*, 100122. https://doi.org/10.1016/j.fsir.2020.100122

[14] Kumar, K., & Al-Besher, A. (2022). IoT enabled e-learning system for higher education. *Measurement: Sensors*, *24*, 100480. https://doi.org/10.1016/j.measen.2022.100480

[15] Marunevich, O., Kolmakova, V., Odaruyk, I., & Shalkov, D. (2021). E-learning and m-learning as tools for enhancing teaching and learning in higher education: a case study of Russia. In *SHS Web of Conferences* (Vol. 110, p. 03007). EDP Sciences. https://doi.org/10.1051/shsconf/202111003007

[16] Mauryan, K. C., & Sakthi, R. S. (2020). Amelioration of Hybrid Power System Using IOT. *Int. Acad. J. Sci. Eng*, *7*(2), 1-5. https://doi.org/10.9756/IAJSE/V7I2/IAJSE0703

[17] Muteba, K. F., Djouani, K., & Olwal, T. O. (2020). Deep reinforcement learning based resource allocation for narrowband cognitive radio-IoT systems. *Procedia Computer Science*, *175*, 315-324. https://doi.org/10.1016/j.procs.2020.07.046

[18] Prasanth, G., & Rajesh, S. (2016). Optimization of Tribological behaviour of Al6061 Hybrid Metal Matrix Composite in Braking Applications. *International Journal of Advances in Engineering and Emerging Technology*, *7*(1), 145–153.

[19] Racovita-Szilagyi, L., Carbonero Muñoz, D., & Diaconu, M. (2018). Challenges and opportunities to eLearning in social work education: Perspectives from Spain and the United States. *European Journal of Social Work*, *21*(6), 836-849. https://doi.org/10.1080/13691457.2018.1461066

[20] Rahman, M. W., Islam, R., Hasan, A., Bithi, N. I., Hasan, M. M., & Rahman, M. M. (2022). Intelligent waste management system using deep learning with IoT. *Journal of King Saud University-Computer and Information Sciences*, *34*(5), 2072-2087. https://doi.org/10.1016/j.jksuci.2020.08.016

[21] Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *Wiley interdisciplinary reviews: Data mining and knowledge discovery*, *10*(3), e1355. https://doi.org/10.1002/widm.1355

[22] Su, J., He, S., & Wu, Y. (2022). Features selection and prediction for IoT attacks. *High-Confidence Computing*, *2*(2), 100047. https://doi.org/10.1016/j.hcc.2021.100047

[23] Thies, J., Zollhöfer, M., Theobalt, C., Stamminger, M., & Nießner, M. (2018). FaceVR: Real-time gaze-aware facial reenactment in virtual reality. *ACM Trans. Graph*, *37*(2), 1-15. https://doi.org/10.1145/3182644

[24] Tudor Car, L., Kyaw, B. M., & Atun, R. (2018). The role of eLearning in health management and leadership capacity building in health system: a systematic review. *Human resources for health*, *16*(1), 44. https://doi.org/10.1186/s12960-018-0305-9

[25] Vijayalakshmi, R., & Jayasimman, L. (2018). A survey on impact of IoT-enabled E – learning services, in: *International Journal of Computer Sciences and Engineering, 06*(02), 178–183.

[26] Yousif Elfatih Yousif. (2023). Smart Learning Based on Internet of Things, *International Journal of Research Publication and Reviews, 4(*4), 142-146.

[27] Zahedi, M. H., & Dehghan, Z. (2019, February). Effective E-learning utilizing Internet of Things. In *2019 13th Iranian and 7th National Conference on e-Learning and e-Teaching (ICeLeT)* (pp. 1-6). IEEE. https://doi.org/10.1109/ICELET46946.2019.9091671

Authors Biography

I. Rufia Thaseen, born in 1991 in Tamil Nadu, India, am a research scholar at B.S. Abdur Rahman Crescent Institute of Science and Technology. She holds a master's degree in Computer Applications, completed in 2020. With over 3 years of experience in the IT industry, she currently serves as a consultant in an IT company. Her research interests are Machine learning and IoT.

Dr.S. Shahar Banu is working as an Associate Professor in the Department of Computer Applications at B.S. Abdur Rahman Crescent Institute of Science and Technology, Chennai. She has 26 years of experience in teaching, research and administration. She has published more than 35 papers in highly reputed International, National Journals and Conferences, 3 book chapters and 2 patents. Her research interests are Data mining, Software Engineering, Machine learning, and Healthcare. She has delivered guest lectures and Seminars. She has acted as an External Examiner for PhD Viva voce examination at Bharadhidasan University and M Tech and MSc project viva voce examinations at the University of Kerala. At present, she is guiding 3 PhD scholars and 4 MCA and 2 BCA final year projects.