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IoT Based EEG Device for Monitoring Student's Brain Activity Using Ensemble Method in Online Classes

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Abstract

In online learning environments, the need to monitor student engagement to achieve desired learning outcomes is foundational to any pedagogy for effective online teaching. With the absence of in-person supervision, keeping track of student attention in remote classes is quite arduous, if not impossible. This paper proposes an IoT-based EEG device for the real-time assessment of students' brain activity to measure and possibly improve students' attention levels in virtual classes. An ensemble machine learning (ML) study, specifically an artificial neural network (ANN) approach, is employed to investigate the relationship between student performance and EEG data. The study shows the performance of students is negatively correlated to the delta power and the theta/alpha ratio, the common EEG metrics for mental fatigue and drowsiness, respectively, for the student. An IoT-enabled EEG device provides teachers with real-time, precise, and unbiased data regarding the student's cognitive attention levels, via a reporting system. Thus, this research demonstrates that the proposed system, utilizing EEG and ANN ensemble-ML methods, can predict attention levels in real-time, enabling timely intervention for students who are disconnected. The study opens the door to the use of advanced BCI systems in teaching to maximize student attention.

Keywords: EEG Signals, Online Learning, Internet of Things, Machine Learning, Ensemble Learning.

1 Introduction

Conventional classrooms are evolving into virtual platforms due to the rise of virtual education, which presents both advantages and disadvantages. The COVID-19 pandemic has compelled the majority of schools, universities, and institutions to adopt online learning, expand the number of online courses, and administer online exams, resulting in an increase in the prevalence of distance learning (Bashir et al., 2021). In virtual classrooms, the lack of physical presence and in-person interactions affecting the real-time student engagement and their attention (Hu, 2022). The continued use of internet resources has driven students into cognitive demolishment, which may impact all cognitive qualities such as memory, perception, and concentration. The lecture's format has a significant effect in students' understanding as well as cognition over online classes. It's critical to narrow this disparity and provide the greatest

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learning opportunities through a practical, efficient monitoring strategy that may yield insightful data on students' engagement in online classes (Ong & Quek, 2023). Google Meet, Cisco Webex, Microsoft Teams, Zoom, Adobe Connect, and other comparable applications are used by the majority of schools, colleges, and institutions to track their students' attention during online classes (Kansal et al., 2021). Students' attention must be maintained in online classes to maximize learning results. Teachers can quickly gauge a student's attentiveness by observing their facial expressions, body language, and participation in classroom discussions. However, these signs are sometimes absent or very weak in virtual environments. The lack of high-quality equipment and high-speed Internet exacerbates the issue. Students miss important lecture portions as a result of returning to the virtual classroom. Furthermore, the effects of the epidemic affect their attention at home, and students struggle to concentrate during online classes (Muthuprasad et al., 2021). This is why having a strong education system is crucial so that teachers can identify children who may be uninspired, inattentive, or experiencing difficulties and provide timely interventions and support (Villegas-Ch et al., 2023).

Numerous initiatives have been made to investigate new educational technology (Willermark & Gellerstedt, 2022). The new evaluation mechanisms, such as computerized evaluation and teacher feedback, as well as automated attendance, are the focus of these technologies. Numerous attempts have also been undertaken to create technology-based systems for monitoring and encouraging student participation in the classroom. The application of AI has facilitated the development of efficient training and educational course approaches (Chu et al., 2022). Teachers have utilized AI-based student evaluation tools to assist in analyzing and evaluating students' overall performance (González-Calatayud et al., 2021). To visualize and analyze student behavior, which is crucial in assessing academic success, many systems have turned to computer vision. Smart homes and cities, smart grids, innovative education and intelligent transportation are all examples of the cyber-physical systems that are part of the IoT, which is enhanced by sensors and controllers. Selecting sensors and measuring techniques is a complex procedure that involves multiple factors. The physical foundations of signal acquisition can also be applied to the measurement of physiological indicators. Many options arise when comparing the measuring technique to the particular sensors (Cubillos-Calvachi et al., 2020).

In order to understand how the study's outcomes are impacted, the article will highlight the connection between the levels of concentration and excitement that were assessed using eye tracking technology and Heart Rate (HR), a stress measuring method. Finding dependencies, or links, between students' knowledge and physiological processes is the aim of this research work. This study attempts to determine correlations between students' test scores and their heart rates during the testing process in this study. It is assumed that stress levels may rise during testing, which will cause an increase in heart rate.

This research explores the integration of ensemble machine learning techniques and Internet of Things (IoT)- enabled electroencephalogram (EEG) devices for monitoring and enhancing learner engagement in online learning environments. This new methodology utilizes live brain activity data to evaluate cognitive metrics related to attention, mental fatigue, and alertness, in conjunction with student performance metrics. The study employs an ensemble Artificial Neural Network (ANN) model to assess student engagement and predicts with significantly higher accuracy compared to legacy techniques such as facial expression analytics and self-reports. The introduction of IoT in educational contexts provides efficient and non-intrusive frameworks for real-time monitoring of student attention, encouraging dynamic adjustments to educator pedagogical approaches. This study exemplifies how machine learning and IoT serve as key facilitators in the construction of adaptive educational contexts, aiming to improve learner performance and enhance the learning experience in online educational environments.

2 Literature Review

Attention is essential in day-to-day life. It is essential to remember someone's name in a loud atmosphere to avoid mistakes in a high-pressure work environment. Over time, attention can fluctuate, and a sudden drop in focus can have severe consequences, including an increased risk of car accidents, medical errors, and industrial mishaps. Considering the practical applications of attention, real-time tracking of attentional states might be beneficial. Awais et al. studied 22 individuals to distinguish between alert and sleepy phases, using an EEG (with 20 channels of dry electrodes) and a driving simulator. Three stages of the study were carried out. The familiarisation step involves introducing the participants to the simulator without collecting any data. During the second training step, individuals were required to wear an EEG cap and become acquainted with the simulator for ten minutes. After that, the participants engaged in 80 minutes of Monotonous Driving (MD), travelling at 80 km/h. Using visual characteristics, such as facial tone, eye blink rate and duration, facial emotions, and movements like yawning and nodding the head, drowsiness-related activities were identified during the MD phase video recording to categorize occurrences of interest. They also used self-rating on the Karolinska Sleepiness Scale (KSS) at the start and end of the MD phase. The P3, P4, P7, P8, C3, O1, Cz, and O2 electrodes showed significant differences in signal amplitude between self-reported alert and drowsy states (Moon et al., 2019). Additionally, they revealed that SVM achieved 80.60% accuracy in distinguishing between alert and sleepy phases, and that variations in delta, alpha, and theta frequencies were observed in the EEG at every 10-minute frame. The Supplementary offers a more comprehensive synopsis of this research, which is considered a representative sampling of the detailed literature.

Below is Table 1 detailing various ranges for brain electrical frequencies. The recordings of these signals were also accomplished by utilizing the Open Vibe program for collecting, analyzing, and structuring the information exchanged within the system. An order-4 Butterworth band-pass filter operates within a frequency range of zero. A frequency range of 1 hertz to 100 hertz was employed for filtering the recorded signals, which were sampled at a rate of 256 samples per second. The EEG instrument used in this study is the Emotiv Epoc X headset, equipped with fourteen channels for data collection. Every single electroencephalogram record underwent cleaning using the Artifact Subspace Reconstruction technique, serving both a practical and reliable function for artifact removal, capable of recovering signals beyond twice their standard deviation range.

Table 1: Status of brain using brain frequency range

Brain frequency type	Bandwidth Range (Hz)	Purpose and status of brain
Delta	0.50 to 2.75	Deeply meditating and sleep
Alpha	7.50 to 11.75	Relaxing or thinking normal
Beta	13.00 to 29.75	Focusing or thinking intently
Gamma	31.00 to 49.75	Conscious and perception thinking
Theta	3.5 to 6.5	Sleeping or meditating

Although the majority of these research capture EEG signals in a laboratory setting and compare circumstances in which participants are distracted by outside stimuli to settings in which they are not, these findings have been repeatedly confirmed. The following are typical conclusions drawn from these studies:

1. The brain waves that are most closely associated with attention are theta (4–8Hz), alpha (8–13Hz), and delta (0–4Hz). Numerous investigations have demonstrated an association between attention and increased mid-frontal theta activity, decreased central and parietal delta activity, and decreased frontal and parietal alpha power.
2. The brain's fronto-central, occipital, and parietal regions exhibit non-periodic EEG activity that is associated with attention.
3. Machine Learning (ML) can classify focus and distraction-related EEG data with up to 89% accuracy.

The researchers Musthapa et al. Proposed a comprehensive design framework incorporating Internet of Things technology in educational settings, creating a dynamic learning atmosphere. Utilizing state transition charts, this framework depicts numerous personalized and adaptable educational scenarios recommended by the system during its interaction with both instructors and students, based on their current levels and existing knowledge (Mustapha et al., 2022). The research was conducted by Zhang et al. A proposal has been introduced regarding an Internet of Things-driven smart learning environment solution. Systemic findings involve employing a photodiode named Bai for capturing illumination information and utilizing an internal resistance thermometer known as DS18B20 to gauge both room temperatures and ambient lighting levels (Zhang & Li, 2021).

Banu et al. have presented an IoT and cloud computing-based design for a smart campus system (Revathi et al., 2020). The methodology employed by the authors to illustrates the way the integration between IoT and cloud computing infrastructure may successfully reorganise traditional teaching and learning approaches, hence facilitating interaction among educators and students as well as between various objects and related devices. Idrees., have proposed the effectiveness of the human-machine interface is largely dependent on IoT solutions' ability to gather, process, and send human biometric data across 5G networks. EEG biometric authentication is highlighted in this investigation, which examines the various biometric authentication techniques used in IoT systems. Due to its stability, universality, and uniqueness, EEG data have expanded beyond traditional BCI solutions to be used in a wider range of domains, particularly in neuromarketing and neuroscience. The main emerging markets in which EEG biometrics are used in the context of the IoT (Idrees & Idrees, 2022).

Emerson., have claimed that the capacity to design effective and captivating learning experiences is a defining element of game-based settings and online multimedia learning. During the past ten years, developments in sensor-based technologies are eye tracking and facial expression analysis—have made it possible to leverage multimodal data streams for analytics education. The more comprehensive awareness of game-based learning, the detection of online student behaviour, and the facilitation of individualised learning are all potential outcomes of teaching analytics, which works with multimodal data gathered during students' interactions with fun learning environments. Hence, for comprehensive learning analytics, in addition to the eye tracking technique, various kinds of sensors (such as temperature, EEG, HR, ECG, GSR, etc.) can also be used to sense student activity. Typically, such instruments must fulfil rigid requirements. Firstly, they need to be an inherent with technical and technological component of the educational process, meaning that they should never, ever limit a student's freedom of movement. The wearing of a wristband is one technique to verify this method (Emerson et al., 2020). According to Zhang, the quick advancement of wristband technology has made it possible to continuously capture neuro-physiological data in settings that are similar to classrooms: natural settings (Lu et al., 2020). Zhang's investigation tried to determine whether high school pupils' academic performance had any neurophysiological correlations. During the course of ten days spanning two weeks, 100 students participated in daily maths and Chinese lessons, and their HR and Electrodermal

Signals (EDA) were recorded using wristbands. Research revealed a strong relationship between students' EDA responses and their academic success as measured by their final exam results (Zhang et al., 2018). Parambil et al., have introduced an Artificial Intelligence (AI) system for tracking students' emotions and attention spans by real-time vision. Teachers were able to monitor student attention levels more precisely and facilitate effective class management with the use of the system's real-time graphical feedback, which might improve student performance. It had the ability to give the pupils numerical scores based on how they focused in class (Parambil et al., 2022).

Kavitha et al., have proposed a way to measure attentiveness with emotional state lecture videos and EEG data that had been captured, in order to determine the efficacy of online learners. ML models showed a favourable link between test performance and attention levels. In addition to examining students' emotional responses, this study offered suggestions for further investigation on recommendation engines and course efficiency (Kavitha et al., 2023). Aljabarti and Othman., have introduced Local-SVM, for determining student engagement in online learning using ML method. It worked better than existing techniques like KNN by local characteristics extracted from the MoveNet model (Aljabarti & Othman, 2023). Parvathy & Smitha, have discussed several automated techniques for tracking student's classroom attention level. Deep learning techniques, facial recognition methods, and EEG data were all integrated into these systems. Various methods were used to calculate the attention levels, including Fisherface Algorithm, HOG descriptor, SVM, DWT, and FAN (Parvathy & Smitha, 2022). Sartika et al., have looked at the challenges faced by distant learning throughout the pandemic and suggested an innovative online monitoring tool. Real-time tracking of student attendance and facial expressions was facilitated by the AI technology. A full-service network with desktop and online apps for teachers and students was produced by the system employing design research techniques and system engineering (Sartika et al., 2022). It describes an Integration of Internet of Things (IoT) and electroencephalography (EEG) within Educational Contexts as a growing interest for Assessing Attention in Students in Online Classes. Systems and techniques such as self-reporting and observation, used in virtual environments to monitor cognitive and attentional states, are rather limited. Unlike self-reporting systems, IoT-enabled self-monitoring systems and techniques such as self-reporting or observation, used in virtual environments for cognitive and attentional state monitoring, are rather limited. Attention and fatigue, directly permitting cognitive assessment in a virtual environment. Recent investigations adopting Machine Learning (ML) approach, primarily Artificial Neural Networks (ANNs), for student engagement conceptualized and classified relevant EEG signals yielding engagement assessment accuracy levels nearing 90% (Pabba & Kumar, 2022). However, in respect to advanced machine learning techniques, use of ensemble learning has been least explored. The objective of this research is to bridge this gap by utilizing ensemble models of ANNs to gauge and predict student attention in real-time in IoT-integrated EEG systems, Automated Devices for Real-Time Attention Monitoring in Online Classes.

2.1 Research Gap

Notably, the utilization of IoT-enabled EEG equipment in the context of real-time online learning session monitoring has initiated interest in the application of ensemble ML models. The prediction accuracy and real-time usability of such models need enhancement. The aforementioned models, primarily SVM and ANN, focus on attention identification with EEG signals, and lack the breadth necessary. Most engagement monitoring techniques remain old, relying on methods such as self-report and facial recognition. In virtual classroom settings, such recognition methods are not only inaccurate but also intrusive (Reddy et al., 2022). The application of combined classifiers, with the added focus of robust accuracy, in educational IoT EEG-systems research remains relatively untouched. This research aims to address the aforementioned issues by employing ensemble ANN architectures on real-time EEG. This provides a high reliability and scalability solution in regard to attention monitoring during synchronous online sessions. (Mindoro et al., 2020).

3 Research Methodology

3.1 Overall Architecture

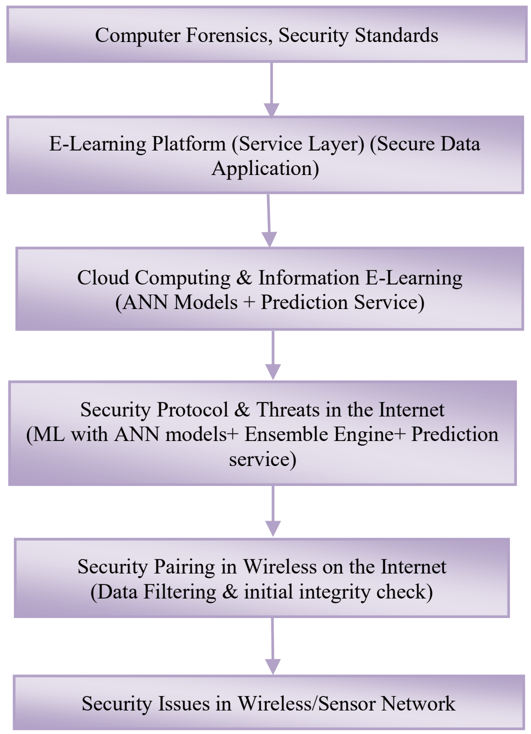

Figure 1: Overall Architecture of an IoT-based EEG device for monitoring students' brain activity using an ensemble method in online classes

For a description of the system's architecture, please refer to the document's Figure 1. It presents a five-layer architecture of an IoT-enabled Brain-Computer Interface (BCI) designed for Secure E-Learning, focusing on the seemingly less addressed aspects of Information Security and Privacy within the JISIS scope. At the most basic level (I), the Flow starts with an IoT EEG Headset (Edge Layer), where instance raw brain data is captured, and the sensitive data is filtered and anonymized on the gateway, which is directly controlled and sets the initial step towards fulfilling JISIS's stringent Anonymity, Secrecy, and Privacy, and Security Issues in Wireless Networks. Then, the information is sent to the second level (II: Network Layer) through Encrypted Transfer (TLS/SSL over MQTT) i.e. Content Protection, and is compliant with the JISIS scope. On arrival, the Ingestion Service receives the data and does an Initial Integrity Check, aligned with Security Protocols and Threat Monitoring is set at this level. In the following Cloud/Server Layer (III) of the architecture, the information is stored in a Secure and Encrypted Data Lake, addressing Security and Privacy in Cloud Computing, and core analysis is conducted here by the Ensemble Engine in the Attitude Score Prediction Service utilizing Secure Voting on ANN Models to maintain the Integrity and Trust of the computational service. This score is provided to the Service Layer (IV), which integrates the data within the E-Learning Platform, thus providing Personal Feedback to the learner, thus fulfilling the E-Learning Internet Service requirement. The entire system is ultimately governed by a Cross-Cutting (V) framework that implements a Security Policy, preserves Audit Logs & Compliance Monitoring, interfaces with Computer Forensics, complies with Security Standards, and facilitates a persistent supervisory layer on security.

3.2 Data Flow Diagram for IoT-Based EEG in the Online Learning Process

Due to safety measures implemented in response to the pandemic, students must complete their tasks remotely as schools remain closed. Students can grasp their lessons effectively if educational standards are raised significantly. A significant reason for declining educational standards lies in students' inability to grasp and absorb course content effectively. Educational authorities employ IoT technology to enhance educational benchmarks within this burgeoning realm of mobile digital environments. The method each learner prefers for studying plays a crucial role in grasping its significance. Students in subsequent schools should adeptly utilize each individual's unique approach to education. When selecting materials for students based on their preferred learning methods, instructors take into account how these approaches will facilitate comprehension of the subject matter and promote academic advancement. Despite potential difficulties, identifying an optimal teaching approach for every individual learner remains crucial.

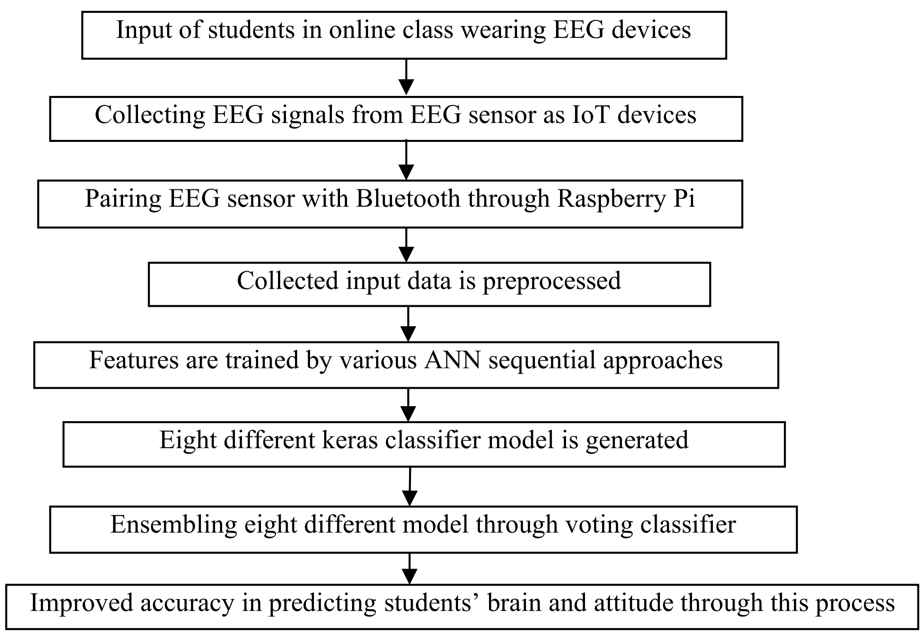

Figure 2: Architecture for IoT based EEG in online learning process

Additionally, this study will utilize ubiquitous connected technologies alongside the Internet of Things for its investigations. Utilizing up-to-date research findings improves this system's forecasting abilities. Educators employ advanced software for organizing diverse learning materials through integration of knowledge and understanding. IoT enables schools to gather and track information from connected gadgets such as bar code scanners, laptops, cell phones, radio frequency identification tags, cameras, electroencephalography machines, and mobile devices. In recent semesters, there has been an increase in the application of Internet-of-Things technology paired with electroencephalography devices within intelligent educational settings designed specifically for remote education experiences as depicted in Figure 2.

3.2.1 EEG Device Acquisition

An A device used for electroencephalography captures electrical signals generated by neurons in the human brain. Devices equipped with sensors track neural impulses as they occur in an individual's head region. Electrodes record brainwave activity, which is then transmitted via an EEG device to either a personal computer or remote servers for analysis. The EEG instrument used during the study consisted of an Emotiv Epoc X 14-channel headband, equipped with non-invasive sensors that recorded electroencephalogram signals directly on the scalp without requiring wetting. This portable setup allowed researchers easy access to continuous brain activity measurements. The device features electrodes positioned on its headband's surface at eight distinct spots, alongside gyroscope units for measuring spatial velocity changes across all axes. Accordingly, based on previous research methodologies, these specific sensors will be installed: specifically, two in the center of the head, located at the front part; three more towards the backside near the top region called the parietal area; followed by another set positioned further down behind where visual processing occurs - known as the occipital zone. The components include: C4, C3, O1, FP2, FP1, P8, P7, and O2.

3.2.2 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.

3.2.3 Dataset Collection

The traditional assessment method employed for evaluating student assignments utilized online platforms enabling them to exchange comments, organize project categories according to personal viewpoints, alongside other functionalities available through these systems. A number of pupils have been selected for participation; they possess diverse educational backgrounds concerning observing live lectures on computers alongside capturing electroencephalogram readings along with tracking neural activity during these sessions. The study involved numerous online video lessons; it analyzed student attitudes based on class participation patterns and assessed their grasp of material through examination of prior learning experiences. Several short clips help illustrate how some learners struggle more than others due to varying levels of attentiveness during class sessions. Therefore. EEG brain wave recordings allow analysis alongside accumulating a binary indicator showing if students comprehend lectures (1 for comprehension; 0 for lack thereof). Approximately twenty-four participants contribute data across six thousand eight hundred thirty-one entries over an extended period of about six months through regular classes. Every recording along with its appendages form part of a unified database known as EEG information. CSV file format is commonly used for storing tabular data in plain text files. Online hours have signified their participation and engagement within virtual classes. Likewise, tracking students' engagement by monitoring their brain activity during lectures reveals this information visually as depicted in Figure 3.

Firstly, we proceed by handling missing values through imputation techniques before scaling individual variables using the robust scalar method. The variables consist entirely of integers; the dataset has been ready for modeling after dividing it into a training set comprising 80 percent of the sample size and a testing set containing the remaining 20%. A conventional machine learning technique is presented alongside an ensemble approach aimed at enhancing student performance evaluation by improving the identification of their skills and reactions following assessment. Additionally, the electroencephalogram data is used to recognize each student's neural state, which aids educators and teachers in monitoring their cognitive activities. Therefore, teachers and support personnel may offer alternative methods such as asking students specific question choices during breaks for those studying particular courses. Thus, an ensemble model enhances student attitudes towards learning by being examined.

```
[ ] 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	PO
0	0	0	4210.641113	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	0.527616	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	2.027946	1.283876	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	0.579658	0.180058	2.265952	1.306188	0.616881	0.506062	
4	0	0	4232.436035	4216.922852	4306.922852	4270.769043	4217.436035	4186.538574	4155.897461	4182.820313	...	2.462552	1.230984	0.573620	0.181081	2.461205	1.522420	0.822598	0.498361	

5 rows × 87 columns

Figure 3: IoT with EEG signal-based skill analyzed students' dataset

3.4 Working of ANN Architecture

Due to the early successes of ANNs, there was a consensus that humans would soon be interacting with brilliant machines. A network of artificial neurons that can calculate any logical statement can be constructed. One of the most fundamental ANN architectures is the perceptron. It is based on a Threshold Logic Unit (TLU), a type of artificial neuron that differs somewhat from the standard artificial neuron. Rather than being binary on/off, values are accounted in terms of input and output counts, and every input connection has a weight assigned to it. Rather than using binary on/off values, the TLU first calculates the input linear functions. Each input connection has a weight assigned to it. The TLU initially computed with the input linear functions shown in Equation 3.4.1.

$$z = w_1 x_1 + w_2 x_2 + \ldots + w_n x_n + b \tag{3.4.1}$$

Where,

X_1, x_2 = Input features

W_1, w_2 = Weight of the input features

b = bias

For conventional linear binary classification, one TLU is sufficient. It calculates a linear function from its inputs and outputs the positive class if the result exceeds a specified threshold. All TLUs have arranged for a single layer, each connected to all inputs, making up a perceptron. This kind of layer is referred to as a dense layer or a fully linked layer. The input layer consists of the inputs. Furthermore, the TLU layer is referred to as the output layer since it generates the final outputs. This perceptron is a multilabel classifier since it can simultaneously classify cases into three distinct binary classes. It can also be applied to multiclass classification. The fully connected layer is illustrated in equation 3.4.2.

$$h_{w,b}(x) = \phi(XW + b) \tag{3.4.2}$$

Where,

X = Features as input matrix

W = Connected weights of the weight matrix

'b = Bias vector per neutron

ϕ = Activation function

A variation of this method that accounts for the network fault is used to train perceptrons. The perceptron learning rule strengthens connections during prediction-making, which lowers error. More precisely, the perceptron learns its predictions by feeding it one training event at a time. The connection weights from the inputs that may have contributed to the accurate prediction are reinforced when each output neuron that generated an incorrect prediction is shown in Figure 4.

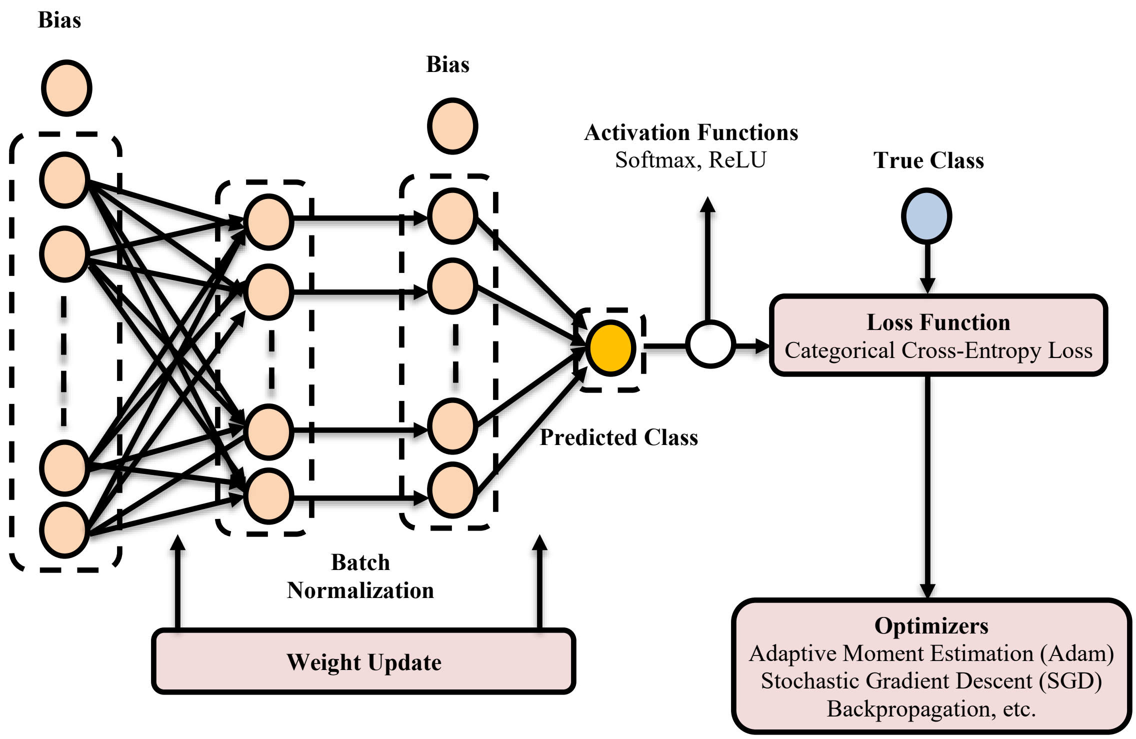

Figure 4: Framework for ANN

It is said that a kernel is a filter which utilized for extracting characteristics from a sample file. The matrix of kernel has traversed the input data and performed dot products with the input data of the sub-region, as well as yields an output matrix representing the dot products. When the dataset under analysis is both extremely imbalanced in terms of class distribution and very dimensional, the problems of feature selection and imbalanced data classification collide. Because the inductive method's performance is used to determine the worth of the feature subset, if the wrapping approach is used for feature selection, the empirical algorithm could result in significant bias. In this paper, a feature selection method is provided for severely unbalanced datasets using an ensemble-based wrapper technique. By training several base classifiers with balanced sample subsets, the proposed technique simultaneously reduces feature selection bias and maximizes data utilization, while retaining the benefits of wrapper-based feature selection.

Attribute weights are computed via a wrapper method. Wrapper approaches employ the inductive algorithm as an evaluation function. With this method, subsets are evaluated in accordance with their predictive accuracy using a classifier, following the sample for statistical resampling or cross-validation.

Because the wrapper method is tailored to the particular interactions between the dataset and classifier, it also yields higher recognition levels than a filter approach. Furthermore, because cross-validation typically uses predicted accuracy measurements, wrappers offer a means to prevent overfitting.

3.5 Algorithm for Ensemble Kernel Classifier

Input: Filtered features of dataset
Output: Ensemble model with improved accuracy
$Begin: Initialize\ EEG\ Device\ (IoT - enabled)$
$While\ (real - time\ data\ streaming)$
$EGG - data = collect\ real - time\ EEG\ data\ from\ device$
$Preprocess\ EEG\ Data$
$Filtered - data = FILTER\ (EEG - Data)$
$Extract\ Features\ from\ EEG\ Data$
$Features = Extract - Features\ (filtered_{data})$
$ensemble - model = LOAD_{MODEL}(ensemble - model)$
$Predicted_{class} = PREDICT\ (ensemble_{model}, features)$
$IF\ predicted_{class} = distracted\ then$
$if\ predicted_{class} == distracted\ then$
$end\ if$
$Repeat\ until\ class\ ends$
end

4 Experimental Result

Derived from empirical studies, an e-learning student database comprises 80 entries after data cleansing; here, 80 percent represents the subset used for training, while the remaining 20 percent constitutes the test set. To assess the effectiveness of our method, we established an experimental environment and analyzed metrics including sensitivity, precision, F1-score, and specificity. The F1 score provides a precise evaluation. Accuracy measures the total number of correct classifications across all predictions, while sensitivity gauges how well it identifies true positives, and specificity indicates its effectiveness at detecting false negatives. This proposed model can predict and evaluate results in comparison to other current techniques, providing essential insights into the effectiveness of the research strategy. A high-end computer with eight cores, 128 GB of RAM, and a 100 GB hard drive was used for our experiments. To take advantage of the feature selection model with keras-based ensembling, an ANN is used in this research. The environment involves necessary dependencies and libraries specifically for the Keras classifier.

```
Point-Biserial Correlation between EEG.AF3 and subject_understood: 0.1257, p-value: 0.0000
Point-Biserial Correlation between EEG.F7 and subject_understood: 0.1288, p-value: 0.0000
Point-Biserial Correlation between EEG.F3 and subject_understood: 0.0600, p-value: 0.0000
Point-Biserial Correlation between EEG.FC5 and subject_understood: 0.0832, p-value: 0.0000
Point-Biserial Correlation between EEG.P7 and subject_understood: 0.1718, p-value: 0.0000
Point-Biserial Correlation between EEG.O2 and subject_understood: 0.1594, p-value: 0.0000
Point-Biserial Correlation between EEG.P8 and subject_understood: 0.1584, p-value: 0.0000
Point-Biserial Correlation between EEG.FC6 and subject_understood: -0.1024, p-value: 0.0000
Point-Biserial Correlation between EEG.F4 and subject_understood: 0.0593, p-value: 0.0000
Point-Biserial Correlation between EEG.F8 and subject_understood: 0.0094, p-value: 0.1104
Point-Biserial Correlation between EEG.AF4 and subject_understood: -0.0672, p-value: 0.0000
Point-Biserial Correlation between POW.AF3.Theta and subject_understood: -0.0822, p-value: 0.0000
Point-Biserial Correlation between POW.O1.Theta and subject_understood: -0.0215, p-value: 0.0002
Point-Biserial Correlation between POW.F4.Theta and subject_understood: -0.0722, p-value: 0.0000
Point-Biserial Correlation between POW.F8.Theta and subject_understood: -0.0795, p-value: 0.0000
Point-Biserial Correlation between POW.F8.Gamma and subject_understood: -0.0375, p-value: 0.0000
```

Figure 5: Feature selection for the obtained feature of electrodes in IoT enabled EEG device

Utilizing compressed environment is an essential role for conducting the experiments proficiently and facilitates the analysis and validates the proposed approach in identifying the student attentiveness in the online learning classes. Figure 5 illustrate the ROC curve which define the proposed keras based ensemble ANN model understanding during its training dataset execute. The outcome with 0.99625 value in ROC curve for keras based ensemble ANN model determines the precise reorganization of electrode value obtained from the IoT enabled EEG device in Figure 6.

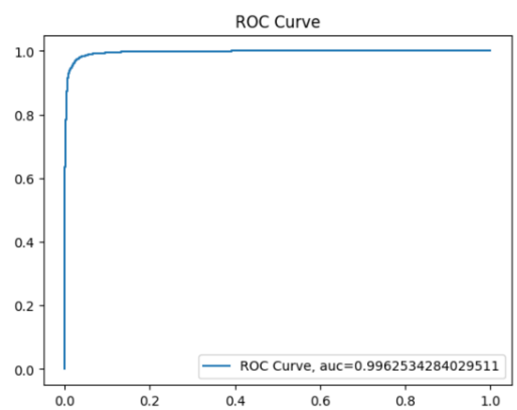

Figure 6: ROC curve for keras based ensemble ANN model

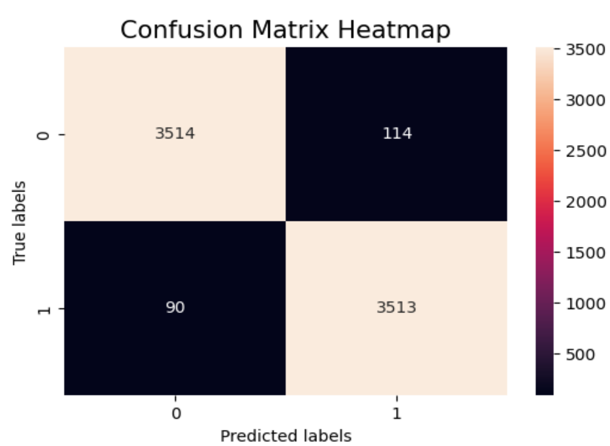

Figure 7: Confusion matrix for keras based ensemble ANN model

The proposed Keras-based ensemble ANN is compared with an ensemble with logistic regression, an ensemble with Neural Network, and the traditional ANN method. Evaluation of the proposed model is done through testing the dataset and determined through a confusion matrix, and the confusion matrix for the Keras-based ensemble ANN is shown in Figure 7.

Table 2 illustrates that the Keras-based ensemble ANN method has performed well in predicting student brain performance as well as reaction datasets. Generally, the Keras-based ensemble ANN method achieves a relatively higher accuracy than the ensemble with logistic regression and the ensemble with Neural Network and traditional ANN methods. Moreover, the Keras-based ensemble ANN method has generated high accuracy for predicting students' attentiveness through the EEG signal, and their performances were analyzed by teachers and staff. Hence, each model with a Keras-based ensemble ANN method is investigated.

Table 2: Confusion matrix metrics value for distinct ML methods

ML classification methods	Accuracy	Recall	Precision	Sensitivity	Specificity
Keras based Ensemble ANN	97.18	97.50	96.86	0.9750	0.9686
Ensemble with logistic Regression	96.87	97.10	96.67	0.9710	0.9665
Ensemble with Neural Network	96.99	97.20	96.78	0.9720	0.9677
ANN	96.54	96.60	96.49	0.9660	0.9649

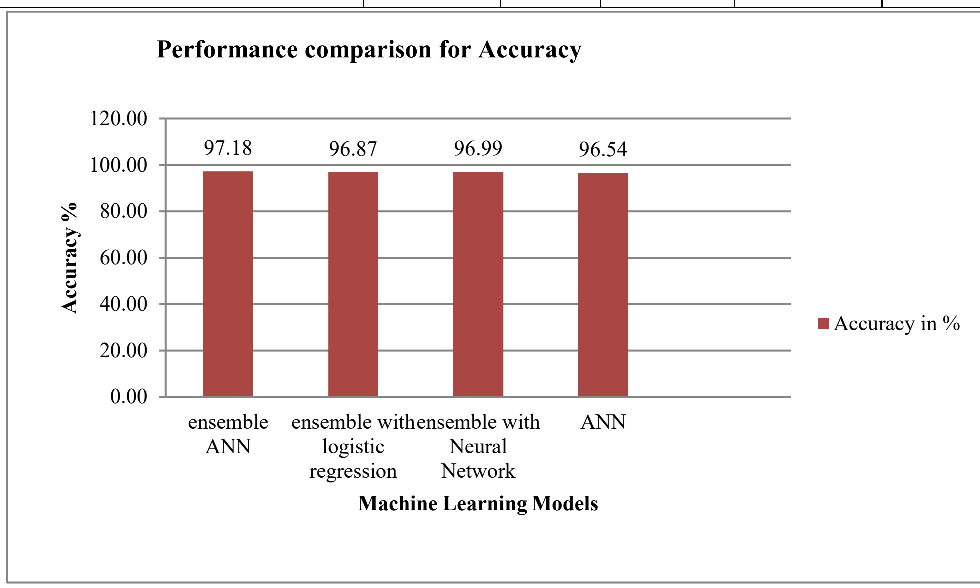

Figure 8: Accuracy comparisons of various ensemble method and ANN method

Figure 8 illustrate the accuracy of proposed keras based ensemble ANN method is 97.18% that comparatively higher than other ensemble LR algorithm, ensemble NN algorithm and traditional ANN methods are 96.87%, 96.99% and 96.54% respectively. This assist in identifying the student attentive detection precisely using keras based ensemble ANN method.

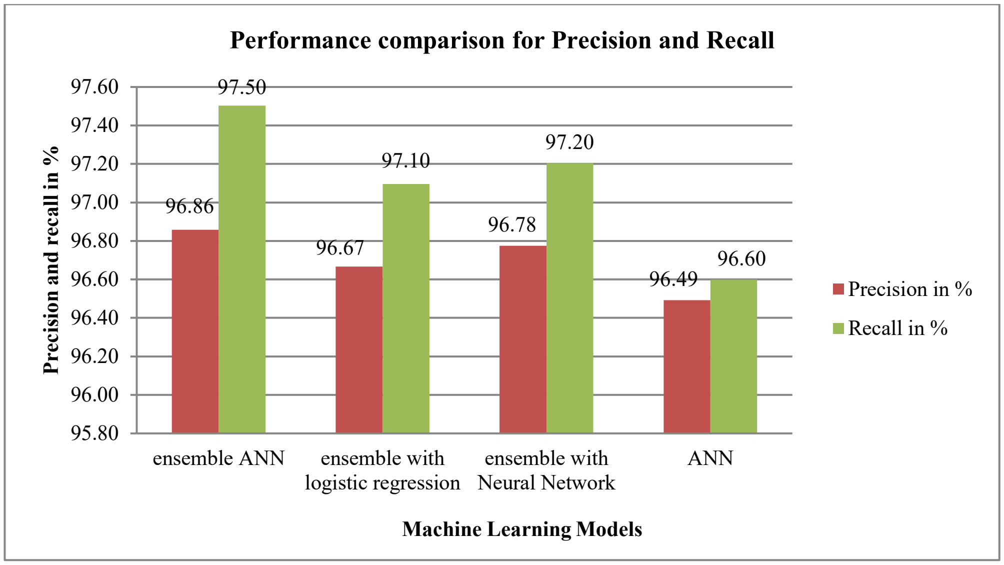

Figure 9: Precision and Recall comparisons of various ensemble method and ANN method

Figure 9 illustrates the precision and recall comparison of recall (true positive rate) and precision (false positive rate), which are 97.50% and 96.86%, respectively. These values are high compared to other ensemble methods and the traditional ANN method. Moreover, these metrics proved that the detection of students' attentiveness is more precise than other ML methods.

Table: 3 Normalized performance comparison of existing models

Model	AUC	MCC	Log Loss	PR AUC
Keras Based Ensemble ANN	99.62	94.45	54.50	98.67
Ensemble with Logistic Regression	96.55	93.11	63.20	97.82
Ensemble with Neural Network	97.00	93.87	62.00	97.93
Traditional ANN	96.00	91.22	70.10	97.48

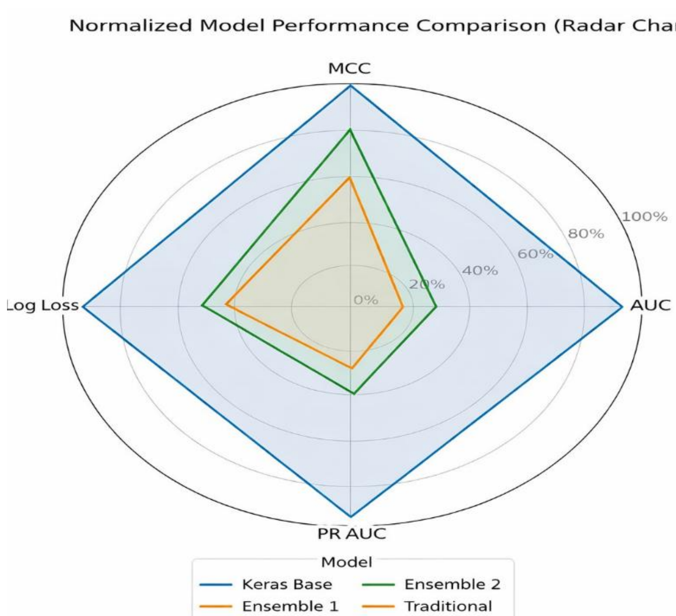

Figure 10: Normalized model performance comparison (Radar Chart)

To interpret the above Table 3 and Figure 10, which describe the machine learning models, as presented, the following evaluations were performed: Keras-Based Ensemble ANN, Ensemble with Logistic Regression, Ensemble with Neural Network, and Traditional ANN. There are four metrics in evaluation: AUC, MCC, Log Loss, and PR AUC. The Keras-based Ensemble ANN performed better in all 4 metrics. Other models were performing well. Log Loss metrics, particularly Those Using Novels with Logistic Regression and Conventional models, excelled compared to the Keras-based model. These values are supported by the Keras-based Ensemble ANN, having commensurate values for AUC, MCC, Log Loss, and PR AUC. AUC and MCC values were predominantly stronger. The Keras-based Ensemble ANN showed more prominent coverage of all four metrics, surpassing that of all other Ensemble models. The Ensemble with Logistic Regression and Neural Network models showed moderately lower performance across the 4 metrics, while the Traditional ANN model lagged behind all others, particularly in the AUC and Log Loss metrics. This suggests that the Keras-based Ensemble ANN model provides the best overall performance, accuracy, and consistency across a range of performance metrics compared to the other models.

5 Conclusion

The primary focus of this study was on detecting student engagement using Internet-of-Things technology; its application in an e-learning environment proves advantageous. Undoubtedly, advancements in educational technology, driven by Internet-of-Things applications, will enhance our understanding of teaching methods. Thus, by utilizing Internet-of-Things technology, the performance of an electroencephalogram device improves its ability to transmit signals into environments conducive for more innovative education systems, thereby enhancing cognitive function and memory recall significantly. Education's progress fosters people skilled and knowledgeable enough to excel. Therefore, these institutions must understand the importance, value, and applications of Internet-of-Things technology, with a specific focus on enhancing student learning through digital platforms. Furthermore, they suggested utilizing Internet of Things-based clever learning techniques to improve predictive capabilities in online education, particularly in terms of student engagement levels. Using an ensemble neural network framework built on Keras, which combines predictions from eight distinct Keras-based artificial neural networks, significantly enhances predictive power compared to both soft-voting ensembles and conventional machine learning techniques in terms of precision and reliability.

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