# Intelligent Tutoring Systems Powered by Generative AI: Advancing Personalized Education and Overcoming Challenges

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***Abstract*— Brain signals analysis can be applied to students to identify their subject- or topic-specific struggles while they are listening to lecture videos. This re- search work proposes a threshold-based anomaly detection algorithm to identify the topics that cause students the most distress by analysing a dataset available at https://www.kaggle.com/datasets/wanghaohan/confused-eeg/data. Firstly, it identifies the index and timestamp of distress data points of students' brain signals, extracts the respective portion of transcribed textual content, given as prompt to ChatGPT or Bard via application programming interface (API) calls, get back the answers, and display it in a pop up window to the students. The proposed generative artificial intelligence (Gen AI)-powered intelligent tutoring system (ITS) captures almost 99% of confusion points and source confusion topic in brain signals as it uses context- aware algorithm thereby improving leaners' clarity on the source confusion topic after reading the pop-up window content generated by Gen AI.**

***Keywords—brain signals, intelligent tutoring system, confusion, chatbots, prompts, Gen AI.***

## I. INTRODUCTION

The analysis of brain signals through EEG technology provides educators with critical insights into the cogni- tive states of learners. Moreover, it opens the possibility to detect their confusion during the screening of instruc- tional videos. By targeting the effective use of particular educational content and consequently building person- alized AI-based support mechanisms such as ChatGPT or Bard it can boost educational outcomes.The precise EEG-based confusion detection, noisy data handling, and possible privacy concerns during data collecting are the major challenges. Also, the extend to which generative AI can enhance clarity is heavily dependent on the quality of the input and responses produced. Although the combination of neuroscience and intel- ligent tutorial systems shows promising potential for the future, more research is needed to overcome these difficulties. The proposed research investigates how brain signal analysis is used to improve learning while students struggle with specific subjects. By scanning real-time brain signals, this research aims to track deviations from normal patterns, revealing challenges in understanding the topic that is currently being listened by the student. It proposes a method to map confusion timestamps in electroencephalogram (EEG) signals to lecture video timestamps and relates the respective confusion topic by applying context-aware algorithms on the transcribed video content and prompting the AI chatbots like Bard or ChatGPT to provide immediate clarification and support on the confused topic.

### *A. Major Contributions*

This research paper applies a proposed Gen AI- based ITS on a confused EEG dataset obtained from https://www.kaggle.com/datasets/wanghaohan/confused-eeg/data. Originally, this dataset was collected from 10 students, each of whom watched 10 distinct subjects' lecture videos while their brain signals were recorded. The signal values of eight brain waves—alpha1, alpha2, Beta1, Beta2, Gamma1, Gamma2, Theta, and Delta—were captured at various intervals and stored in Excel spreadsheets. As a result, a comprehensive dataset encompassing 10 individuals, 10 lecture videos of different subjects, and numerous data points for each of the eight brain waves is generated. The major contributions of this research work are as follows:

*1) Confusion Identification:* This research work pro- poses a threshold-based anomaly detection algorithm to identify the index of points in the EEG signal series that are abruptly changed from the nor- mal range in the respective eight brain waves. Later, these data points will be converted to timestamps by multiplying them with their respective points per second metric given in Table. I.

*2) Topic Association:* This research work proposes a context-aware algorithm that uses the timestamp of abrupt wave pattern to extract the appropriate portion of transcribed textual content of the video (using https://flixier.com/tools/video-to-text) at the same timestamp, which is the reason for this deviation.

*3) Confusion-Topic Mapping:* This research proposes a methodology that queries the ChatGPT or Bard via an Application Programming Interface (API) call to model the topic by passing the ex- tracted transcribed textual content to it.

*4) Large Language Model (LLM) or Gen AI In- tegration:* After the identification of the topic of confusion, the proposed approach pauses the video at that position and queries the LLMs or ChatBots like ChatGPT or Bard through API to clarify the topic of confusion to the learners.

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This research paper is organised as follows: Section II provides a comprehensive overview of notable previous works in this domain. Section III elaborates on the pro- posed ITS presented in this paper. Section IV delivers the results and discussion of the research findings. Finally, the concluding remarks along with the future work are given in Section V.

## II. Related Works

The methodology for emotion recognition through emotional responses and Hjorth parameters (activity, mobility, and complexity) is explained in [1]. Research has consistently demonstrated a strong correlation be- tween a student's learning effectiveness and their level of attention [2]–[5]. In the realm of e-learning, where direct supervision from educators is absent, students have frequently reported experiencing difficulties in maintaining focus [6]. Adopting modern teaching approaches in rural areas faces various challenges that demand innovative teaching methods in rural communities [7]. An approach that suggests a methodology to regulate brainwave states could enhance concentration and reduce stress levels [8]. Term-relevance estimation using Brain Signals (TRPB) showcased that relevance detection using brain signals was possible thereby allowing the relevance judgments acquisition irrespective of any other user interaction [9]. The study explained in [10] utilized machine-learning techniques to successfully decode se- mantic categories and individual words from EEG and Magnetoencephalography (MEG) recordings of participants engaged in a language task. As online education continues to grow, there is a need to understand when and why students choose to take or avoid online courses which is given in [11]–[13].

An approach that calculates the mental state, how effective and interesting the learning course is, and the appropriate methods for tutoring is explained in [14]. Numerous research studies indicate that intentionally controlling our brainwave states can strengthen our ability to focus and alleviate stress levels [15], [16]. The Depression Recognition Neural Network is designed for detecting major depressive disorder (MDD) detection, and AlexNet and GoogleNet for sleep disturbance identification, which were outlined in [17]–[21]. Binary and multi-label classification was employed in clinical research, cognitive function studies, motor imagery (MI) processing, emotion recognition (ER), and brain disorder investigations, encompassing brain injury, attention dis- orders, and multiple sclerosis [22]–[25]. Computational neural models were used to model learning predictions and monitoring behaviour in the medial prefrontal cortex (mPFC) and anterior cingulate cortex, as elucidated in [26]. Besides, the recent research [27]–[32] focused on assessing the students' cognitive engagement, neuro- enhanced education system effects, and methodology to improve the student's attention during learning.

In concise, there hasn't been a thorough exploration of EEG signals when assessing the emotional and cognitive states of students engaged in e-learning. This is coupled with the inadequacy of personalized solutions to keep learners engaged in monotonous online environments. As a positive note, detecting brain signals can reveal how attentive participants are, but nobody is using this information to provide timely feedback. It is evident that tech-based learning is more about employing the technology than addressing cognitive difficulties faced in particular subjects. Also, the existing brain health studies on training programs or stress relief in learning settings have hardly any real-life applications. There's still a gap in processing EEG/MEG data to provide feedback that is rich in information for learners. There's potential to employ multi-world classifications for naturalized feeding roles, allowing us to gauge stress levels and understanding concurrently, but that's not ideal. Unfortunately, neurology-enhanced systems fail to apply effective methods for assessing the intensity of cognitive engagement dynamically.

## III. Proposed Gen AI-Powered Intelligent Tutoring System Using EEG Signals

In neuroeducation, Machine Learning(ML) techniques have emerged as powerful tools for analyzing brain activity and extracting valuable insights into learner aptitudes, cognitive processes, and emotional states. The proposed approach has four modules as given in Fig. 1: Confusion Identification, Topic Association, Confusion- Topic Mapping, and LLM or Gen AI Integration.

### A. *Confusion Identification*

This module tries to identify the data points that showcase drastic changes in their consecutive values that are the indicators of confusion using a threshold-based anomaly detection algorithm.

### B. *Topic Association*

Subsequently, this module transcribes the respective lecture videos along with the timeline using Flixer. It means that it associates the time and its transcribed sentences using a context-aware algorithm.

### C. *Confusion-Topic Mapping*

This module is trying to associate the identified confusion data points with the appropriate transcribed sentences in the video in a simple manner. For instance, if a person-0 or subject-0 watches a lecture video-0 of length 140 seconds duration and the brain signal kit collects 144 data points for the eight brain signals, then duration per data point is calculated as follows: 140 seconds/144 = 1 second which is points per second(approximately). Further, if the confusion data point is the 12th point in the data set, then 12 x 1 second= $12^{th}$ second in the video. Subsequently, the transcribed sentence, which is at the $12^{th}$ second in the timeline, is the source of confusion for person 0 or subject-0. Then the context-aware algorithm extracts this portion of the content, queries the ChatGPT or Bard, and identifies the topic of confusion.

### D. *Large Language Model (LLM) or Gen AI Integration*

Consequently, this module takes the topic that is responsible for confusion as input, formulates the query, and sends it to LLM models like ChatGPT and Bard to clarify the source of confusion. This process is explained in Fig .2

The chosen dataset contains EEG signal data from 10 students, recorded while watching 10 curated educational videos on various subjects, with each video trimmed to 2 minutes for a focused analysis.

**Algorithm.1: Confusion Detection and Resolution**

1: Convert EEG signals to digital format

2: Segment signal into epochs of length $\Delta t$

3: for each epoch $e_i$ do

Extract frequency $f$ for each brain wave type
Delta wave ($0 \leq f < 3$ Hz): Check if $f \in [0, 3)$
Theta wave ($4 \leq f < 7$ Hz): Check if $f \in [4, 7)$
Alpha wave ($8 \leq f < 11$ Hz):
  Alpha1 ($8 \leq f < 11$ Hz): Check if $f \in [8, 11)$
  Alpha2 ($8 \leq f < 11$ Hz): Check if $f \in [8, 11)$
Beta wave ($12 \leq f < 29$ Hz):
  Beta1 ($12 \leq f < 29$ Hz): Check if $f \in [12, 29)$
  Beta2 ($12 \leq f < 29$ Hz): Check if $f \in [12, 29)$
Gamma wave ($30 \leq f < 100$ Hz):
  Gamma1 ($30 \leq f < 100$ Hz): Check if $f \in [30, 100)$
  Gamma2 ($30 \leq f < 100$ Hz): Check if $f \in [30, 100)$
Detect anomaly if $f$ / normal range
if anomaly detected then
  Compute timestamp $T_i$ as:

$$T_i = \text{Index}_i \times \text{Points per second}$$

  Store $T_i$ in confusion points list
end if
end for
for each timestamp $T_i$ do
  Extract text from transcribed video at $T_i$
  Query language model via API for topic
  Retrieve and provide clarification to learner
end for

The 10 videos selected were on the following topics:

- Video 0: Nuclear Physics: an explanation about the charge on an electron.
- Video 1: A mathematical concept of Limits.
- Video 2: The mathematical concept of Inequalities.
- Video 3: The topic being taught is Progression, which is a branch of Mathematics.
- Video 4: This is the continuation of the previous video. It explains how to derive the sum of n natural numbers.
- Video 5: The video is about the Electric field, more precisely about the Electromagnetic Theory.
- Video 6: This video is about Nuclear Fission and Nuclear Fusion, a concept of Physics.
- Video 7: The concept of Physics being explained is the Electric Circuit.
- Video 8: In this video, the professor is explaining the digital waveform of a signal.
- Video 9: This video is also based on the concepts of Physics: Transmission and Reception.

The videos were chosen and shown to every individual as stated in [33]. In this particular experiment, the Mind-set used three electrodes: one placed on the forehead and two placed on the ears. The electrode on the forehead is positioned over the prefrontal cortex, a brain region involved in various cognitive functions, including emotion regulation. The electrodes on the ears serve as reference points for the voltage measurements. These positions ensured optimal signal acquisition and minimized interference from other sources. The Mind- set converts analog voltage fluctuations from electrodes into digital signals, segments them into 1-second epochs for analysis, and classifies these into different wave types to assess brain activity. The brain signal normal ranges are given as follows:

- Delta Wave: 0-3 Hz, Deep sleep
- Theta Wave: 4-7 Hz, Creativity, dream sleep, drifting thoughts
- Alpha Wave (lower and higher): 8-11 Hz, Relaxation, calmness, abstract thinking
- Beta Wave(lower and higher): 12-29 Hz, Relaxed focus, high alertness, mental activity, agitation, anxiety
- Gamma Wave(lower and higher): 30-100 Hz, Mental activity, agitation, anxiety

The data information of the columns of the dataset are as follows:

- Column 1: The subject ID, telling about the person ID, ranging from 0 to 9.
- Column 2: The Video ID, it ranges from 0 to 9 for each individual.
- Column 3: It is the first sensor value denoting the Attention level of the individual. It is a measure of mental focus.
- Column 4: The next sensor value represents Mediation. It is a measure of the calmness of the individual.
- Column 5: This column represents RAW, i.e., raw EEG signal values.
- Column 6: It contains values of Delta signal operated at 1-3 Hz of Power spectrum. It represents deep sleep.
- Column 7: It contains values of the Theta signal operated at 4-7 Hz of the Power spectrum. It represents creativity, dream sleep and drifting thoughts.
- Column 8: It contains values of Alpha 1 signal operated at Lower 8-11 Hz of Power spectrum. It represents relaxation, calmness and abstract thinking.
- Column 9: It contains values of Alpha 2 signal operated at Higher 8-11 Hz of Power spectrum. It represents relaxation, calmness and abstract thinking.
- Column 10: It contains values of Beta 1 signal operated at Lower 12-29 Hz of Power spectrum. It represents relaxed focus, high alertness, mental activity, agitation, and anxiety.
- Column 11: It contains values of Beta 2 signal operated at Higher 12-29 Hz of the Power spectrum. It represents relaxed focus, high alertness, mental activity, agitation, and anxiety.
- Column 12: It contains values of Gamma 1 signal operated at Lower 30-100 Hz of Power spectrum. It represents mental activity, agitation and anxiety.

- Column 13: It contains values of Gamma 2 signal operated at Higher 30-100 Hz of Power spectrum. It represents mental activity, agitation and anxiety.
- Column 14: This column represents the predefined label of whether the subject is expected to be confused.
- Column 15: This column represents the user- defined label whether the subject is confused or not.

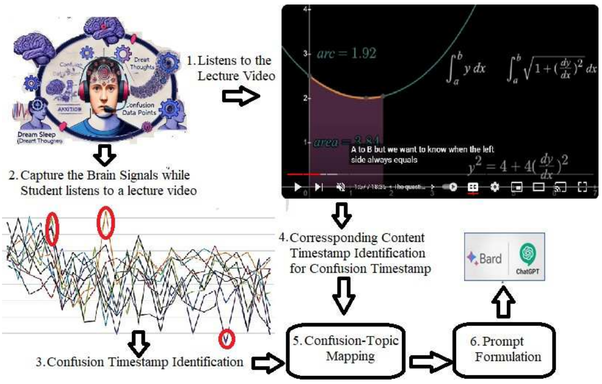


Fig. 1. Proposed Gen AI-Powered Intelligent Tutoring System using EEG Signals


Fig. 2. Transcription and Prompt formulation for Video1 at 12th second for 12th confusion point in the EEG signal

TABLE I. POINTS PER SECOND CALCULATION FOR THE DATASET

| VN | S | TP | L | PPS |
|---|---|---|---|---|
| V0 | S1 | 144 | 141 | 1 |
| V1 | S2 | 140 | 143 | 1 |
| V2 | S3 | 142 | 123 | 0.86 |
| V3 | S4 | 122 | 117 | 1 |
| V4 | S5 | 116 | 146 | 1.25 |
| V5 | S6 | 123 | 124 | 1 |
| V6 | S7 | 116 | 117 | 1 |
| V7 | S8 | 112 | 114 | 1 |
| V8 | S9 | 124 | 126 | 1 |
| V9 | S10 | 122 | 123 | 1 |

## IV. RESULTS AND DISCUSSION

After getting the data about the 10 persons regarding all the videos from https://www.kaggle.com/datasets/wanghaohan/ confused-eeg/data, a table named Table.I with five columns is created: The first column gives the video number(VN), the second column gives the corresponding brain signal series to be associated(S), the third column gives the total number of data points that are taken from the dataset(TP), the fourth column gives the length of each video in seconds(L) and the last column gives the points per second that are calculated by dividing the fourth column by the third column(PPS).

For a first-person (person-1), the graphs were plotted against each signal considering the first 25 data points and hence analyzed where the graph becomes abrupt or the points with maximum and minimum deviations from the normal range. Hence, these were the points of discrepancies as per the confusion identification module. A table named Table II for person-1 is shown below where the first column is brain signal(BS), the second column is Confusion points identified by Confusion identification module(CP) (timestamp in the brain signal) and the third column is corresponding video and second(timestamp in the video for the confusion point). For instance, in the first record of Table. II, the confusion point in Delta signal(first column) is observed at series S5 at point number 23(second column) then the corresponding video is v4(refer to Table. I) and the respective seconds in the video that make the confusion can be identified by a point which is 23 multiplied by PPS for S5 is 1.25(refer to Table. I) that leads to 23 x 1.25=29 sec. it means that the topic discussed during 29th second of video 4 is a source confusion topic for which prompt is formulated and queried through API calls to chatbots bard or ChatGPT and the results are popped up to the person-1.

TABLE II. REFERENCE TABLE SHOWING DISCREPANCY POINTS AND ITS CORRESPONDING VIDEO POINTS FOR PERSON – 1

| BS | CP in BS | Video and Sec |
|---|---|---|
| Delta | S5 Pt23; | Video 4 – 29 sec (23x1.25 from Table.I) |
| Theta | S2 Pt14; | Video 1 – 14 sec |
| Alpha 1 | S2 Pt14; | Video 1 – 14 sec |
| Alpha 2 | S2Pt14 S6Pt4 | V ideo1–14sec V ideo5–4sec |
| Beta 1 | S2Pt11 S2Pt14 S6Pt5 S6Pt23 | V ideo1–11, 14sec V ideo5–5, 23sec |
| Beta 2 | S2 Pt14; | Video 1 – 14 sec |
| Gamma 1 | S2Pt14 S6Pt4 S6Pt5 S6Pt18 | V ideo1–14sec V ideo5–5, 6, 18sec |
| Gamma 2 | S2Pt14 S6Pt5 S6Pt11 | V ideo1–14sec V ideo5–5, 11sec |

Inference for Fig. 3: In Video 4, the teacher is writing in line 1 and then waits for a few seconds. He then says bear with me for a second and starts writing at 29 seconds. The person is not interested in those few seconds and his attention is affected at second no. 29 and hence changes in graph. There are abrupt changes in the Video1 graph. As the video is related to a mathematics topic called limits, maybe the person is not confident of the topic being taught or he may be finding it difficult to concentrate. As Beta signals denote high mental alertness and anxiety, it can be inferred he is feeling agitated of the topic being taught. As video no.5 started, there was already a figure drawn on the board and the teacher started directly with a formula. Any person, seeing such a thing would have drifting thoughts and his thinking would be in some other direction and hence the graph is abrupt and rapidly changing.

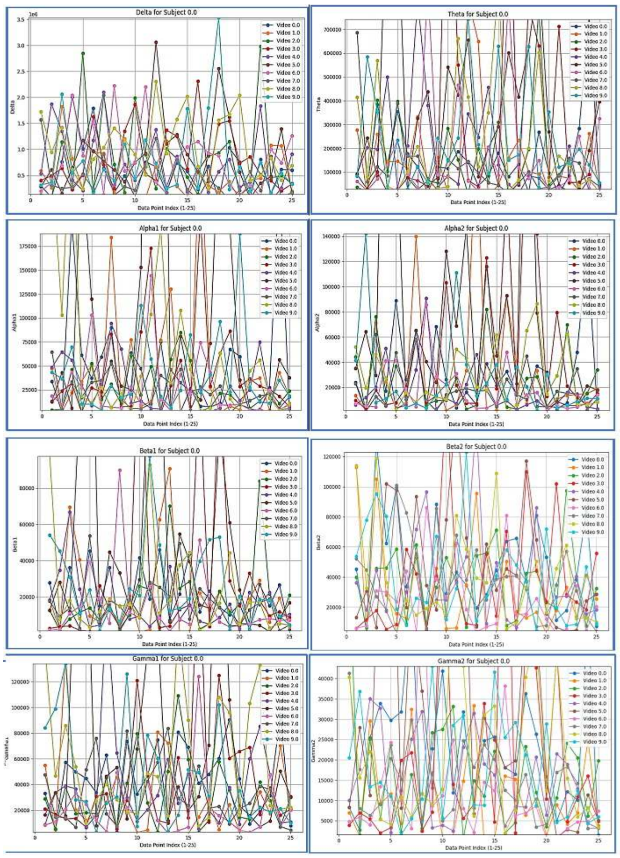


Fig. 3. Person – 1(Subject-0.0) – All Videos -X axis is 25 data points and Y axis is signal power spectrum – from left to right and top to bottom: (i) Delta; (ii) Theta; (iii) Alpha-1; (iv) Alpha-2; (v) Beta-1; (vi) Beta-2; (vii) Gamma-1; (viii) Gamma-2 Signals

## V. Conclusions And Future Work

The research work starts from the phase of an- alyzing the different brain waves and decoding their meaning. It proceeded with relating the brain waves to some physical and mental activity. The significance of the different brain waves is analysed and later the data of the videos is used to draw different graphs. These graphs were used to study the points of focus. These points of focus helped in finding out the significance of the different waves and their relation to the mental activity of a person. These results were then merged for the inferences of all the videos so that a common or generalized inference could be delivered by each of the signals. From these, it is possible to distinguish the brain signals and find out the state of the student just by analyzing the brain waves. These brain wave data can later be used to find out the difficulties a student is facing in the curriculum. The difficulties can then be solved by prompting chatbots like Bard or ChatGPT. The results give a good overview of the signals and their meanings. The proposed Gen AI based ITS has the potential to change the education system and make it better and more advanced than before. In the future, it is planned to design a headset along with the integration of different dis- tressed mental state identification modules and their respective recovery strategies thereby enhancing the attention of the students.

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