

Developing Frugal Internet of Things with Backpropagation Neural Network for Predicting Impact of Gemini Artificial Intelligence on Student Meditation and Relaxation [†]

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[†] Presented at the 2024 IEEE 6th Eurasia Conference on IoT, Communication and Engineering, Yunlin, Taiwan, 15–17 November 2024.

Abstract: With the rapid development of generative artificial intelligence (AI) technologies, large language models have been developed and used in education. In this study, we employ the Google Gemini AI tool (version 1.0) to annotate teachers' programming of teaching materials. When students learned these annotated teaching materials, the ThinkGear ASIC module (TGAM) and galvanic skin response (GSR) sensors were deployed to measure student mindfulness meditation, relaxation levels, and learning stress. We constructed a backpropagation neural network (BPNN) model with three hidden layers to predict student concentration and relaxation levels using GSR data and the time that students spent answering questions. In the developed system, we deployed a Node-Red dashboard to monitor all sensing data and predict results for mindfulness meditation and relaxation levels. The results were stored in an SQLite database. The BPNN model effectively predicted students' mindfulness meditation and relaxation levels. For multiple-choice questions about teaching materials, the mean absolute error (MAE) of the BPNN model was 14.29 for mindfulness meditation and 10.54 for relaxation.

Keywords: Gemini AI; TGAM; GSR



Academic Editors: Teen-Hang Meen,
Chi-Ting Ho and Cheng-Fu Yang

Published: 17 April 2025

Citation: Tseng, C.-K.; Chan, C.-H.; Lin, L.-S.; Wang, F.-J.; Yao, K.-H.; Hsu, C.-W. Developing Frugal Internet of Things with Backpropagation Neural Network for Predicting Impact of Gemini Artificial Intelligence on Student Meditation and Relaxation. *Eng. Proc.* **2025**, *92*, 10. <https://doi.org/10.3390/engproc2025092010>

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1. Introduction

Positive emotions increase student motivation to learn and focus on their goals for satisfactory learning outcomes [1,2]. On the other hand, negative emotions undermine student learning motivation, divert their attention, and result in negative learning efficacy. Stress in learning leads to poor memory performance [3]. In addition, free recall and recognition abilities decrease by more than 30%, indicating stress negatively affects learning outcomes.

Electroencephalography (EEG) is used to investigate academic learning. For example, a ThinkGear ASIC module (TGAM) is used to compare learning attention while using different media [4]. Participants using text-based media had the highest attention levels in the study. Additionally, there were significant differences in attention performance between students with active and reflective personalities when learning through video media. Gaikwad utilized brainwave features to build a machine-learning model to predict student online learning outcomes [5]. EEG and galvanic skin response (GSR) signals indicated that students' emotions, attention, and interest were lower in online education compared with in-person teaching [6]. Dong deployed GSR to measure students' varying levels of different emotional responses under the same teaching model [7]. Generative AI has been widely

used in education, including in curricula and teaching [8]. Imran suggested using Gemini AI to customize student learning and related needs [9]. Additionally, teachers use it to create appropriate teaching materials and provide feedback with evaluations of learning differences. In the application of artificial intelligence (AI) to learning performance, artificial neural networks (ANN) are commonly used to predict students' learning performance. ANN is used to predict college students' learning performance based on input variables such as time spent on content [10]. Huang et al. analyzed the impact of emotions on college students' online learning performance efficacy and used ANN to predict learning outcomes [11].

Based on the previous research, we developed a backpropagation neural network (BPNN) model based on input variables from GSR sensors and response times. The model predicted student attention and meditation levels. Additionally, to effectively improve student learning outcomes, Gemini AI was used to provide teaching materials with detailed explanations to assist students' learning.

2. Proposed System

We used the message queuing telemetry transport (MQTT) protocol for data transmission, as shown in Figure 1. In the MQTT protocol, the Arduino Uno was used as the publisher, transmitting DHT11 and GSR data through the D1 mini to the MQTT broker on the Raspberry Pi 4. The TGAM model processes the participants' brainwave signals via Bluetooth. In the system, Node-RED acted as the Subscriber, displaying the sensor data in real time on the dashboard user interface (UI) and storing the data in SQLite. Additionally, in the system, Gemini AI communicates through Google API to generate teaching materials with detailed explanations on the Raspberry Pi 4.

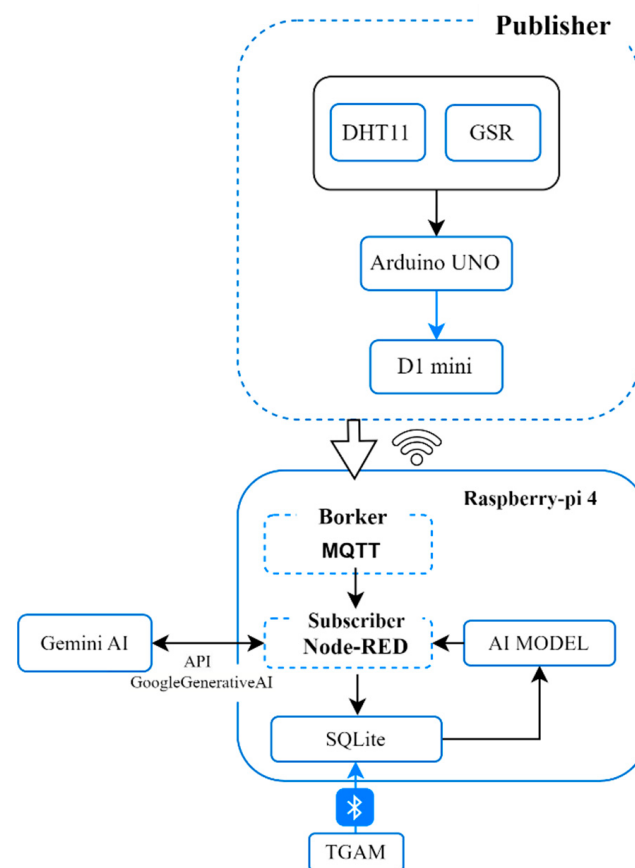


Figure 1. Proposed system.

The users of the system are teachers and students who can log into the Node-RED web interface. Students can log into the webpage by entering their student ID and selecting the question type and difficulty of the questions in Python version 3.10.8 programming, as shown in Figure 2. Additionally, teachers access three web pages on the Node-Red dashboard: the first page is for creating Python programming questions for students, the second page is for viewing real-time physiological data of the students, and the third page is for reviewing the student answer history. In this study, we used GSR and TGAM to collect students' physiological data to train the BPNN model. The GSR sensor was used to monitor students' skin resistance. The TGAM module was used to monitor students' ATT and MED, which were calculated using the eSense algorithm [12].

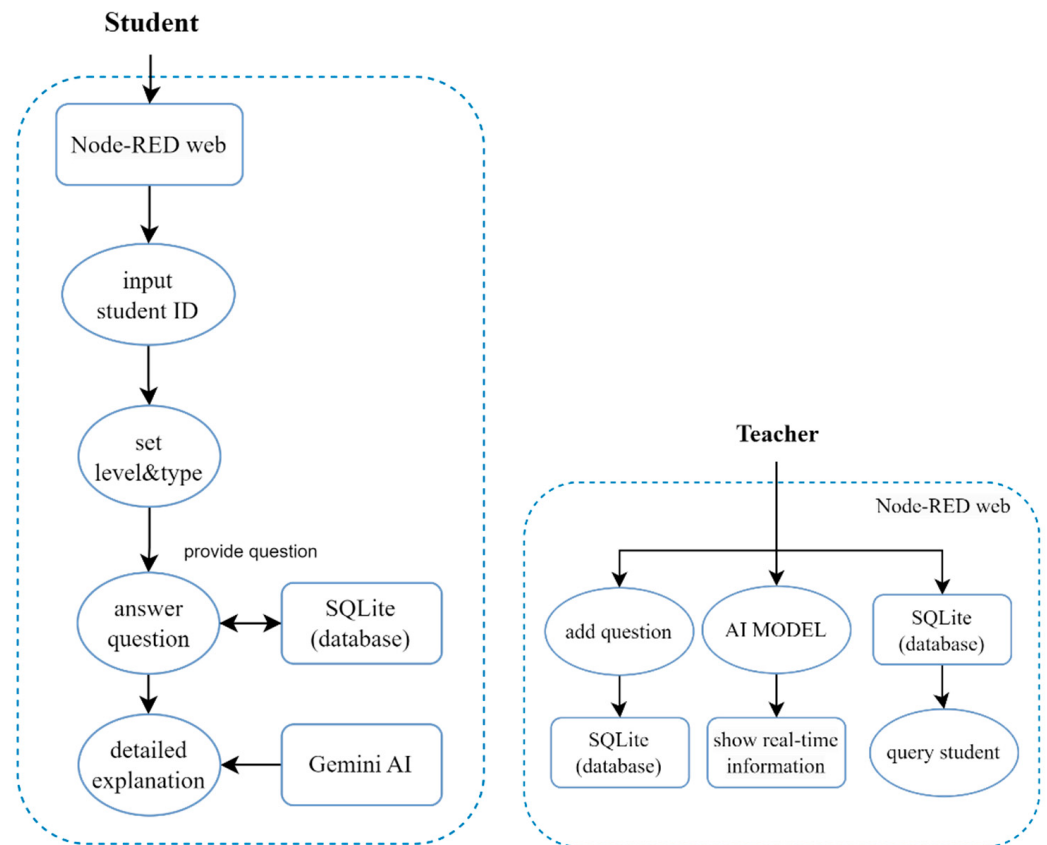


Figure 2. Operational flow of developed system.

In the developed system, the BPNN model was configured with three hidden layers, as shown in Figure 3. Based on Ref. [13], we input four features: the minimum value of GSR (GSR_MIN), the maximum value of GSR (GSR_MAX), the mean value of GSR (GSR_MEAN), and the standard deviation of GSR (GSR_STD). Additionally, we measured answering time as a feature. Five features were used to train the BPNN to predict students' attention and meditation time. Before training BPNN, we normalized the data to the range [0,1]. These features passed through three fully connected layers containing 32, 64, and 128 neurons, respectively. We selected the rectified linear unit (ReLU) to capture the non-linear relationships in the data. Additionally, to avoid overfitting, we added a dropout layer at a rate value of 0.5 in the BPNN model. The BPNN's weights were adjusted using the Adam optimizer with a learning rate of 0.001. The BPNN model was trained for 100 iterations, and the mean absolute error (MAE) was chosen as the loss function.

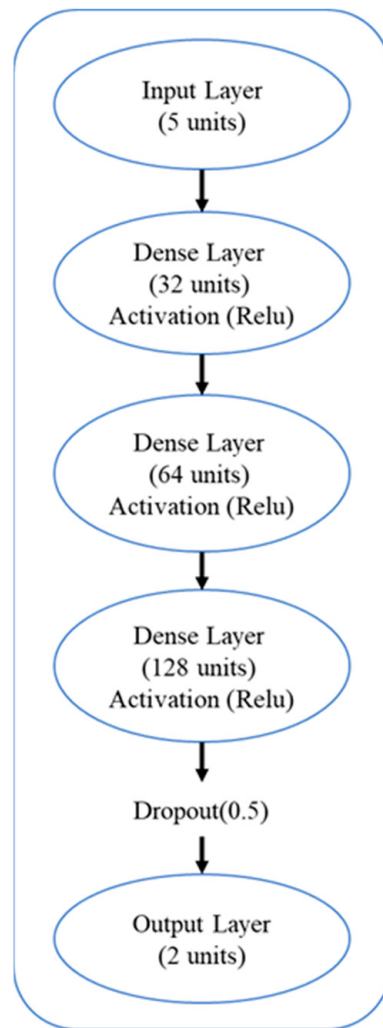


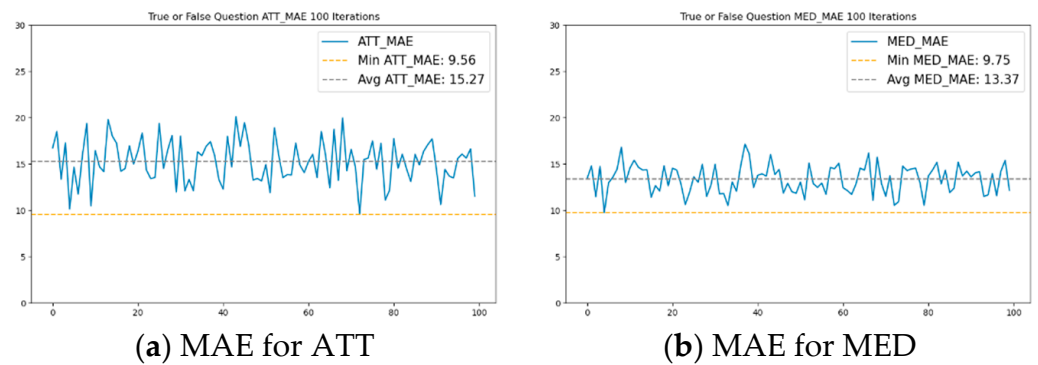
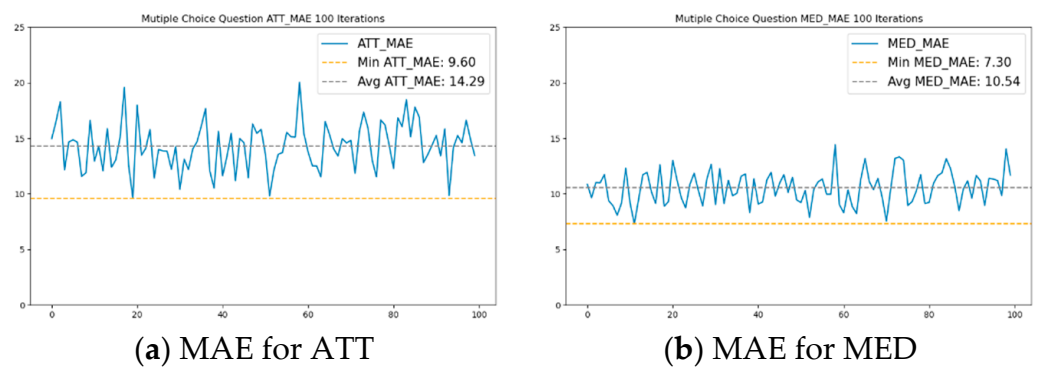
Figure 3. Proposed BPNN model structure.

3. Experiment

In the experiment, the Python questions were categorized into true or false (TF) quiz questions, multiple-choice (MC) questions, and question difficulty (easy, medium, and hard). First, the developed system collected the data from the GSR sensor and response times for answering questions from two participants (Table 1). Additionally, we trained two BPNN models: one for RF questions termed TF-BPNN and one for MC questions termed MC-BPNN. To eliminate noise, we removed data where brainwave signals were Poor Signal > 100, ATT and MED = 0, and GSR values > 550. We improved the method used by enhancing the features of GSR to increase the input data. On the other hand, the ATT and MED values were averaged for each question as FF-BPNN and MC-BPNNs' targets. The data in Table 1 were collected on 2024/08/22. For TF-BPNN, the MAE of ATT and MED were 15.27 and 13.37 with the lowest values being 9.56 and 9.75, as presented in Figure 4. For MC-BPNN, the MAE of ATT and MED were 14.29 and 10.54 with the lowest values being 9.6 and 7.3, as presented in Figure 5.

Table 1. Extracted features.

Time	GSR_MAX	GSR_MIN	GSR_MEAN	GSR_STD	Answer Time	ATT	MED	Type	Degree	Subject ID
14:06:28	527	526	526.5	0.707	9	38	67	T/F	Simple	Subject 1
14:11:35	465	451	456	7.81	9	45.3	28.6	T/F	Normal	Subject 1
14:15:35	479	470	474.7	3.35	13	39.7	50.5	T/F	Difficult	Subject 1
14:18:21	474	470	472	1.5	9	36	58.6	MC	Simple	Subject 1
14:22:10	478	472	477.1	1.96	9	44.1	53.3	MC	Normal	Subject 1
14:23:32	472	455	464	8.54	6	43.3	49.3	MC	Difficult	Subject 1
15:11:40	340	334	338	3.46	5	15.6	72.3	T/F	Simple	Subject 2
15:15:45	296	277	295.2	3.41	10	36.6	51.9	T/F	Normal	Subject 2
15:18:23	355	343	350.5	5.2	17	75.5	67.3	T/F	Difficult	Subject 2
15:23:23	258	237	247.5	12.12	13	11.5	32.6	MC	Simple	Subject 2
15:26:00	260	242	251.1	5.69	15	41.4	35.4	MC	Normal	Subject 2
15:31:16	272	260	266.3	5.68	11	79.3	33	MC	Difficult	Subject 2

**Figure 4.** Prediction results for ATT and MED for T/F questions.**Figure 5.** Prediction results for ATT and MED for multiple-choice questions.

To verify the effectiveness of the TF-BPNN and MC-BPNN, we experimented with two participants, using GSR. In the experiment, the room temperature was controlled between 25 and 27 °C. The participants completed the test based on the three-level Python programming questions. The experiment results are shown in Table 2.

Table 2. Predicted result.

Time	GSR	ATT	MED	Type	Degree	Subject ID
15:59:09	417	33.4	43.4	T/F	Simple	Subject 1
16:09:31	460	31.7	45	T/F	Normal	Subject 1
16:13:32	475	31.5	46.6	T/F	Difficult	Subject 1
16:00:46	452	32.6	46.8	MC	Simple	Subject 1
16:11:28	478	31.7	45.8	MC	Normal	Subject 1
16:14:55	484	31.5	45.4	MC	Difficult	Subject 1
16:19:21	196	29.8	69.7	T/F	Simple	Subject 2
16:20:35	183	28.9	71.8	T/F	Normal	Subject 2
16:23:04	105	25.5	94.8	T/F	Difficult	Subject 2
16:25:59	135	57.9	46.3	MC	Simple	Subject 2
16:28:03	106	58.2	47.8	MC	Normal	Subject 2
16:31:14	91	52.8	47.1	MC	Difficult	Subject 2

The TF-BPNN and MC-BPNN accurately predicted ATT and MED. As the questions' difficulty increased, Subject 2's GSR values gradually decreased, indicating a greater pressure in answering difficult questions. To alleviate the pressure, the developed system integrated Gemini AI to annotate Python teaching materials. For example, after completing these questions, Subject 1 learned teaching materials annotated by Gemini AI and obtained a higher GSR compared to Subject 2, indicating a more relaxed emotional state.

4. Conclusions

The developed system included a GSR sensor for detecting student stress levels and a TGAM device for capturing brainwave data. All data were stored in an SQLite database and displayed the result on the Node-RED dashboard on a Raspberry Pi. Additionally, TF-BPNN and MC-BPNN evaluated student mindfulness meditation and relaxation based on GSR data when using teaching materials annotated by Gemini AI. When students encountered learning difficulties, Gemini AI effectively reduced their learning stress. In the future, it is necessary to integrate low-cost sensors into the system to improve the two BPNNs' prediction accuracy for mindfulness meditation and relaxation.

Author Contributions: Conceptualization, C.-K.T.; methodology, L.-S.L.; software, C.-K.T. and C.-H.C.; validation, C.-W.H.; formal analysis, F.-J.W.; data curation, K.-H.Y.; writing—original draft preparation, C.-K.T.; writing—review and editing, L.-S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Science and Technology Council grant contract NSTC 113-2221-E-227-004-MY2.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The authors do not have permission to share data.

Acknowledgments: This study is supported by the National Science and Technology Council, Taiwan and the National Taipei University of Nursing and Health Sciences, Taiwan.

Conflicts of Interest: The authors declare no conflict of interest.

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