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Article

# Research on interactive english classroom teaching based on biosensor technology: Analysis of biological indicators

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**Abstract:** With the advancement of educational technology, biosensors are becoming valuable in enhancing classroom interactivity and adapting teaching strategies. In English language classrooms, maintaining student engagement and managing learning anxiety is essential for effective learning; traditional methods fail to offer real-time insights into student engagement and emotional states. The objective of the research was to enhance language instruction effectiveness by monitoring learners' cognitive states using biosensor technology. Initially, biosensors were used to collect physiological data such as heart rate variability, eye movement, facial expression, posture, and seating data from students during English language lessons and also gathered over four weeks in a controlled classroom setting. The collected data underwent noise reduction using signal-to-noise ratio (SNR) to improve signal clarity and min-max normalization to scale the data within a consistent range for accurate analysis. Spiking neural networks (SNNs) are integrated with biosensors and areic brain neural processing, enabling dynamic adaptation of teaching content based on physiological signals and enhancing personalized learning by responding to student's cognitive and emotional states. The findings offer that biosensor technology combined with SNNs significantly improves student engagement, reduces language anxiety, and increases learning efficiency. When compared to other weeks, student engagement (30%), cognitive load (10%), task completion efficiency (30%), attention focus (35%), and teacher-student interaction (35%), all showed better outcomes in Week 4. This suggests that biosensor-driven adaptive teaching, powered by SNNs, has the potential to transform interactive language learning.

**Keywords:** biosensor; English; classroom teaching; spiking neural networks (SNNs)

## 1. Introduction

Advanced technology incorporation into education has revolutionized the traditional classroom teaching techniques of the past years [1]. From the many innovations, biosensors represent a highly efficient tool for classroom interaction and engagement. This has given unprecedented opportunities in the context of English language teaching, which requires active participation, emotional involvement, and real-time feedback to fill the gap between teacher and student and foster a dynamic and responsive learning environment [2]. These will provide important insights into a student's emotional state, engagement, and level of stress [3]. With such information provided, a teacher can even make real-time decisions to adjust learning and further personalize teaching in a far more effective way [4]. In an English classroom, where the achievement of communication skills and confidence building are so crucial, such insights could be employed to remove the barriers in the form of anxiety or disengagement with even better learning outcomes. Interactive English classroom teaching through Biosensor technology has several advantages [5]. It identifies responses from the students immediately with the possibility that a teacher can see the effectiveness of the teaching style and alter it accordingly. For example, if biosensor data suggests that a loss of interest in an activity is taking place, a teacher can adjust the method quickly and regain attention [6]. Further, its inclusivity reveals the needs of the diverse learners, which can be those who are not so explicit in their problems through speech. The integration of biosensor technology set the trend toward educational data-driven processes [7]. The intersection of physiological data with pedagogies strengthens educators' understanding of student behaviors and learning processes, creating an opportunity for each student to succeed. The subject of education is undergoing a digital transition; therefore, research on biosensor technology-based interactive English language instruction in classrooms has a lot of possibilities for creativity [8]. The possibility of a biosensor technology revolution in teaching and learning the English language through applications that relate to student engagement, teacher responsiveness, and overall effectiveness in learning [9]. The empirical research would focus on the interaction between technology and pedagogy for contribution to the growing research bodies of using biosensors in education, constituting a basis for further evolutions in the interactive classroom-based teaching methodologies [10]. The objective of the investigation is to enhance language instruction effectiveness in English classrooms by monitoring learners' cognitive and emotional states using biosensor technology.

### Contributions of this research

- The goal of the project was to improve the efficacy of language training by employing biosensor technology to track learners' cognitive states.
- The gathered data was subjected to min-max normalization to scale the data within a constant range for precise analysis and signal-to-noise ratio (SNR) noise reduction to enhance signal clarity.
- The results show that using biosensor technology in conjunction with SNNs greatly enhances learning efficiency, lowers language anxiety, and promotes student engagement.

The paper is organized into several sections: Part 2 covers the related works, Parts 3 and 4 outline methodology and outcomes, and Parts 5 and 6 provide the discussion and conclusion.

## 2. Related works

Traditional approaches to teaching Spanish vocabulary frequently rely mostly on student memory and teacher explanations, both of which were limited by time and space and produce less-than-ideal learning results. The use of biosensing technologies to improve the efficiency of teaching Spanish vocabulary was investigated [11]. The traditional method of teaching languages and repetition intends the benefits of physical activity for improving linguistic and cognitive skills. Biomechanical treatments in teaching English constitute kinesthetic learning methods, movement-based learning vocabulary, postural training, and sensory-motor integration. The experimental outcome demonstrated a dynamic and attractive learning environment [12]. The multimodal data from think-aloud and computer logs was merged to examine instructors' self-regulated learning (SRL) behaviors when creating a class that utilized technology. Random forest (RF) regression analysis results indicate that the optimal combination for explaining a significant percentage of variability in technological pedagogical content knowledge (TPACK) performance was three SRL activities from the logs and two from the think-aloud data [13]. An extensive comparative UX analysis of Open edX and Moodle, two platforms utilized for massive open online course (MOOC) implementations, was presented. Delivery dates, available financial and human resources, and students' familiarity with e-learning platforms were only a few of the non-technological elements that influence an institution's choice of platform [14]. A biosensor-based platform for seeing microorganisms has been developed. Sequencing, Operational Taxonomic Unit (OUT) [15] clustering, and other processes, and visualization tools produce high-definition images from which researchers can examine the $\alpha$-diversity and $\beta$-diversity of microbial communities. The voice network system's unique network structure was introduced in the article. The speech network system's performance requirements were extremely high, as determined by the system's overall design and practical application. A dedicated network was mostly used to analyze the voice network system's performance in real-time [16]. Vital signs have long been measured and tracked using wearable sensors for applications in healthcare and well-being. To illustrate the difficulties encountered by researchers when integrating learning technologies for improved engineering education, it defined the objectives and went over the inclusion and exclusion criteria. Additionally, it offered suggestions for enhancing the instruction and learning of engineering courses in higher education through the use of wearable technology [17]. Academic success depends on one's capacity to obtain the terminology efficiently. To comprehend the course material, students should participate in writing, and discussion exercises and communicate with instructors and peers, they need a strong vocabulary in English. The experimental outcome demonstrated the student's impact on biomechanical interventions in terms of their mental well-being and English vocabulary development [18]. The blended teaching assessment index system was enhanced with artificial intelligence (AI) emotion recognition technology. Emotion recognition was used on students throughout class; they were reminded to maintain the caliber of their learning. Techno-methodological tendencies in education research computational and immersive approaches were identified, along with their implications for interaction analysis (IA) [19]. Students' English writing ability and comprehension were impacted by biomechanics-based physical motions. The randomized controlled trial (RCT) was used to provide biomechanics-based therapies for participants. The result findings indicated that physical activity improves the cognitive functions for successful language acquisition [20]. Across a range of age groups and situations, augmented reality (AR) can improve students' motivation and cognitive abilities. In the form of design principles, the work explored the qualities that were crucial for AR authoring in the classroom. Using design-based research (DBR) [21] and an interdisciplinary team, the goal was to determine how educators would like to develop AR experiences according to their pedagogical requirements. It also sought to explore and provide design principles for AR educational writing. The involvement of children in life events has a significant impact on their social and academic outcomes. To elicit different involvement states, Photoplethysmography (PPG) and motion (IMU) [22] signals were recorded from children's physiological reactions using a commercial smartwatch. The succession of high-notice behaviors varied across presentation levels in an immersive virtual reality (VR) environment using attention data tracked by Electroencephalography (EEG) physiological brainwaves and numerous learning videos [23]. The gathering and evaluation of bio-information was increasingly becoming the most important aspect of the biological sciences. The use of new technologies in educational neuroscience and molecular genomics technologies in educational genomics were two among many examples that have shown how bioinformational techniques could be explored in education research in recent years [24]. A research collection showed the organization forms that have emerged in conjunction with bio-informational research and knowledge generation with education [25].

## 3. Methodology

The advanced biosensors collect a wide range of physiological data from students in a controlled setting of a classroom teaching the English language for four weeks. These sensors measured key physiological indicators such as heart rate variability, eye movements, facial expressions, postures, and sitting patterns, thereby giving an overview of students' physical and emotional states during classes. The collected data was thoroughly preprocessed to ensure its quality and relevance, with noise reduction techniques applied using signal-to-noise ratio (SNR) analysis followed by min-max normalization for scaling the data to a consistent range, thus enhancing clarity and consistency for further analysis. For a sense of the processed data, Spiking neural networks were combined with the biosensors. The SNNs gave a more advanced methodology in data analysis as it was able to mimic how the human brain operates, thus real-time adaptation in teaching methodologies was possible. This dynamic system was designed to continuously monitor and evaluate the cognitive and emotional states of the students and adapt the learning content to these factors. Such customized learning strategies would not only fulfill the requirements of the students but also help in developing a more exciting and less tension-filled classroom atmosphere. In this way, by providing the content of each student based on their emotional and cognitive responses, the intended to develop an in-depth feeling for the material, improve the involvement of the students, and decrease the anxiety that comes with language learning, developing a more effective and emotionally supportive learning environment. **Figure 1** shows the methodology flow.

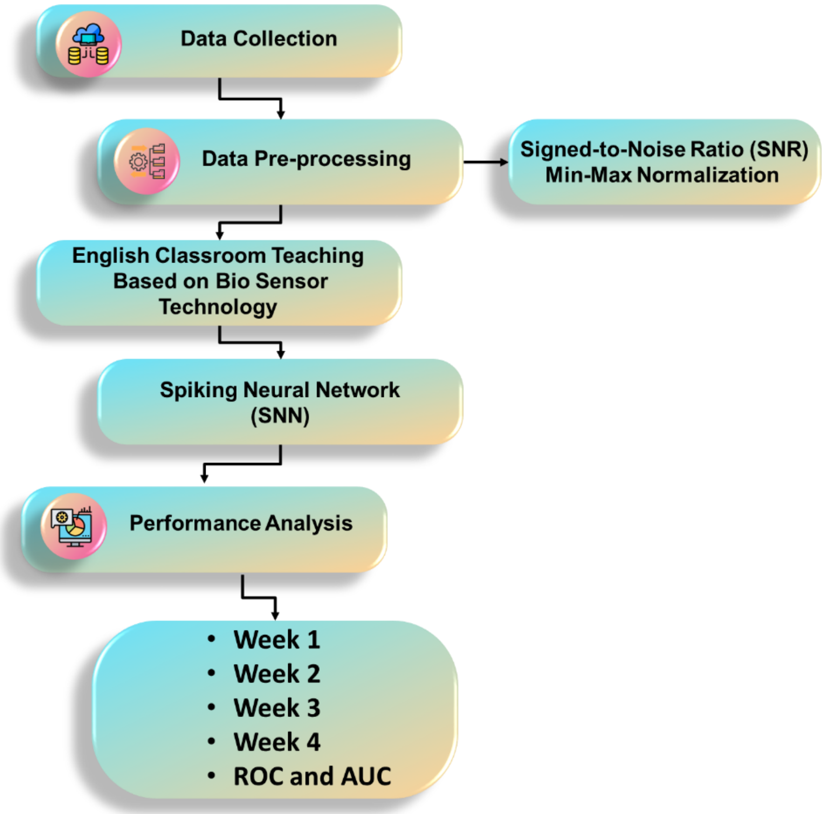


**Figure 1.** The flow of methodological design.

### 3.1. Data collection

A dataset comprised of physiological data collected from students over four weeks (Week 1 to Week 4) of English language lessons in a controlled classroom environment. The data, captured through biosensor technology, includes various physiological indicators such as heart rate variability, eye movement, facial expressions, posture, and seating information. These physiological signals were recorded to assess and monitor the students' engagement levels and emotional states during learning. The utilization of biosensor technology in educational settings would be improved with the help of additional data, guaranteeing more efficient and flexible teaching methods. The data collection intends to provide a more accurate and real-time evaluation of student involvement and emotional well-being. The data processing and analysis were performed to identify patterns and correlations between the students' physiological responses and their learning behaviors, offering a more personalized and dynamic approach to understanding their learning experience.

### 3.2. Data preprocessing

Signal processing, one of the key applications, is involved in noise reduction using SNR, which focuses on the improvement of clarity and quality of signals. The desired signals are increased, and the unwanted background noises are reduced or eliminated to achieve this improvement. In turn, the fidelity and accuracy of the data would improve as well, making the outcome more reliable and easily interpreted for further analysis. Through this filtering technique of the meaningful components of the signal and suppression of the interference, SNR optimization facilitates clear measurements that are significant in applications such as communications, medical diagnostics, and sensor networks. In addition to Min-Max normalization, as an ancillary technique, scales data within a well-defined consistent range, usually from 0 to 1. This eliminates all biases that would likely be generated by intrinsic scales or magnitudes within some measurements. Comparing or doing additional analysis is considerably more equitable when all the data is converted to a single scale using min-max normalization because there is no skewing effect for characteristics with higher numerical values. These noise-reduction and normalization techniques, applied together, synergistically improve overall accuracy, consistency, and robustness in subsequent analyses. They allow more insightful information to be obtained from the data to better understand the underlying patterns and relationships that otherwise could be masked by noise or by differences in measurement scales. This clarity and uniformity in the data will ultimately lead to more reliable results and actionable conclusions in a wide array of scientific, engineering, and practical applications.

- Signal-to-noise ratio (SNR)

The signal-to-noise ratio (SNR) in English classroom teaching using biosensor technology measures the clarity and relevance of physiological signals captured during learning activities. Biosensors help track students' cognitive and emotional engagement, filtering meaningful data from background noise. A high SNR indicates effective teaching strategies and accurate insights into student responses, enhancing personalized learning experiences. The noise $T^2(s)$ always have a stochastic description, while the signal $O_t$ can or cannot. The power of the deterministic signal is defined as Equation (1).

$$O_t = \frac{1}{S}\int_0^S T^2(s)cs| \tag{1}$$

where $T$ is the duration of a period of observation, periodic signals are called by special names, and the signal's period is represented by the interval $T$ in this instance. For instance, the sinusoid $Asin\ 2\pi f_{\circ} s$ has strength $A^2/2$ and a value equal to $A/2\surd$. The value of the correlation function is used to define the power of a stationary stochastic process signal $Q_t(\tau)$ at the origin Equation (2).

$$Q_t(\tau) \equiv \mathrm{E}[t(s)t(s+\tau)]; O_t = Q_t(0)| \tag{2}$$

Here, the expected value is shown by $E\ [\cdot]$. Similar relationships exist between the noise power PN and its correlation function Equation (3).

$$OM = Q_M(0).| \tag{3}$$

Usually expressed as SNR, the signal-to-noise ratio equals Equation (4).

$$SNR = \frac{Q_t}{OM}.| \tag{4}$$

There are two methods to define the signal-to-noise ratio for random variables.

- $W = t + M$, where, the signal, which is a steady $M|$ is a random variable with zero as its expected value. The SNR equals $t^2/\sigma_M^2, |with\sigma_M^2|$ the variance of $N$.
- $W = S + M$ Where $S$ and $N$ are both random variables in this case.

The power of a random variable is equal to its mean-squared value; hence, the signal power is equal to $\mathrm{E}[\mathrm{T}^2]$. Since the noise often has zero mean, consequently, the SNR generation $\mathrm{E}[\mathrm{T}^2]/\sigma_{\mathrm{M}}^2$.

- Min-max normalization

Data normalization is of much importance in the correct interpretation of biosensor readings for effective teaching in the classroom. One of the most frequently used data normalization methods is min-max normalization, where a considered feature's values are transformed into a new range with a given interval; in most cases, the range is set between 0 and 1. This method guarantees that all the relationships between variables in the data analyzed are retained, and it makes it easier to process and interpret signals captured through the biosensor's Equation (5).

$$u' = \frac{u - \min_B}{\max_B - \min_B}(new\_\max_B - new\_\min_B) + new\_\min_B \tag{5}$$

$u'$ is the new standardized value, $u$ is the original value for the feature, $\max_B$ is the highest possible value for feature $B$, $\min_B$ is the minimum value for the features, and $u$ and $new\_\min_B$ are the highest and lowest points for the new range under consideration. This normalization technique can be applied in studies such as English classroom teaching based on biosensor technology to process sensor data efficiently. This ensures consistent scaling of data, allowing improved analysis of student engagement and physiological responses during classroom activities.

### 3.3. Spiking neural networks (SNNs)

Single spiking neurons and the involved computation capacity in their temporal information coding have attracted much interest within the neuroscience domain, due primarily to the fact that these are spiking. Networks of spiking neurons are more commonly known as SNN. They have been shown capable of approximating any continuous equation; therefore, they can be rendered to represent the functionality of any feed-forward sigmoid neural network. This has led to theoretical proof that SNNs, which are based on precise spike timings used for encoding and transmission of information, statistically outperform traditional neurons based on sigmoidal activation functions in terms of potency and efficiency. These computational neuroscience breakthroughs hold tremendous potential for interdisciplinary applications, such as enriching educational environments. Biosensor technology introduced in English classroom teaching might eventually change how educators monitor and respond to student's cognitive and emotional engagement. Such systems, coded with temporal information, will capture the subtlest of student focus shifts, emotional states, and changes in attention levels, thereby bringing to the fore a richer insight into student behavior. Data from such sources could be fed into dynamic teaching strategies to adjust them to best respond to the needs of particular students. The monitoring can further contribute to building a more supportive and responsive classroom environment in which teachers can intervene to improve student learning outcomes and well-being at the right moment. **Figure 2** represents SNN architecture.

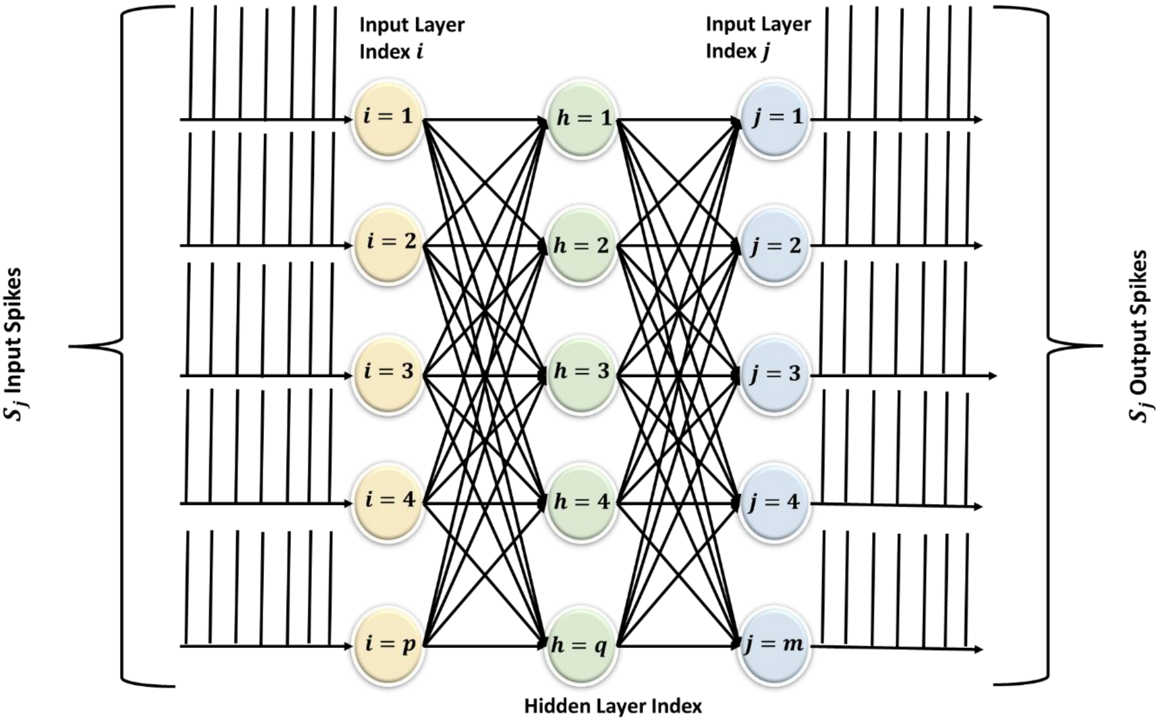


**Figure 2.** Structure of SNN.

- Spike Response Model

An overview of the basic spike-response model is provided for completeness. The state variable $v_j$ describes the condition of neuron $j$. If $v_j$ rises beyond a predetermined threshold, a neuron is said to fire. The firing time $s_j^{(e)}$ is defined by the threshold crossing moment. The collection of all cell $j$ firing periods is represented by the set of threshold crossings over time. In the context of English classroom teaching, biosensor technology can provide novel insights into cognitive and emotional responses during the learning process. This integration of biosensor technology with the spike-response model could enhance the understanding of neural dynamics associated with educational outcomes in Equation (6).

$$\mathscr{F}_j = \left\{s_j^{(e)}: 1 \leq e \leq m\right\} \equiv \left\{s: v_j(t) \geq \theta\right\} \tag{6}$$

The value of the state variable $v_j$ is influenced by two factors. First, the state variable $v_j$ is decreased right after an output spike is fired at time $s_j^{(e)}$ (Equation 7).

$$\Gamma_j = \{i: iPresynaptictij\} \tag{7}$$

The condition $v_j$ of neuron $j$ is impacted by a presynaptic spike at time $s_j^{(e)}$ by the amount $\omega_{ji}\epsilon\left(s - s_j^{(e)}\right)$. While $(s)$ is a kernel function, the weight $\omega_{ji}$ is a factor that determines how strong the connection is. A neuron if's state $v_j(s)$ at time $s$ is determined by the linear superposition of all contributions, $\eta$ simple clarification is probable for the conditions on the right side of the Equation (8).

$$v_j(s) = \sum_{t_j^{(e)} \in \mathscr{F}_j} \eta\left(s - s_j^{(e)}\right) + \sum_{i \in \Gamma_j} \omega_{ji} \left( \sum_{s_j^{(e)} \in \mathscr{F}_j} \epsilon\left(s - s_j^{(e)}\right) \right) \tag{8}$$

The first sum represents the influence that the neuron prior spikes had on its current state. Responding to all presynaptic pulses, the neuron is modeled by the sum of the kernels. Equations (7) and (8) define the generic spike response model. Kernel functions for $\eta\ (\cdot)$ and $\epsilon(\cdot)$. Typically, when $s\ >\ 0$, the kernel $\eta\ (s)$ is not positive; in execution, it takes the form Equation (9).

$$\eta(s) = \eta_0 \exp\left(-\frac{t}{\tau}\right) \mathscr{H}(t) \tag{9}$$

where $\eta_0$ is the relative refractoriness amplitude, and $\mathscr{H}(t)$ is the well-known heavy side function that has a value of 1 for $s\ >\ 0$ and disappears for $s\ >\ 0$. The state variable $v_j(s)$ has a value equal to the threshold at the time of firing, assuming continuous time. Consequently, after every firing occurrence, Equation (9) sets $v_j(s)$ to the value $\theta - \eta_0$. Take note that following a firing instance, the condition variable $v_j(t)$ is reset to zero if $\{0\ =\}$. When a single spike from neuron $j \in t_j$ impinges on neurons, the unweighted postsynaptic potential (PSP) is modeled by the kernel $\in (\cdot)$. This is the mathematical expression that is utilized. Equation (9) shows that the synaptic weight factor $\omega_{ji}$ modulates the PSP's amplitude of Equation (10).

$$\epsilon(t) = \exp\left(-\frac{t}{\tau}\right) \mathscr{H}(t) \tag{10}$$

Alternatively, the postsynaptic potential's excitatory or inhibitory character can be inferred from the sign of the weight $\omega_{ji}$. In this contribution, the latter strategy is utilized. Excitatory PSP, or ESP for short, is a positively weighted PSP, whereas inhibitory PSP (IPSP) for short, is a negatively weighted PSP.

- Theoretical Aspects of SNNs

It is indeed possible to construct networks of spiking neurons that approximate any bounded continuous function in the temporal domain. This capability is grounded in the computational process that was outlined previously, which leverages the unique characteristics of spiking neurons to encode and process information over time. The ability to approximate such functions highlights the computational power of spiking neural networks, especially in scenarios where temporal dynamics are critical. The theoretical foundation for the assertion is provided by Theorem 1, a key result that formalizes and substantiates the claim. Theorem 1 sets the theoretical framework along with conditions such that the constructed spiking neuron networks are capable enough of such an approximation. In addition to verifying the said claim, the theorem points out design rules and some limitations for constructing SNN toward realizations of tasks that demand strict timing and accuracy on the approximated target functions.

**Theorem 1:** *Using $(t + c)$ spiking neurons, where the temporal delays of the spikes are used to encode the analog inputs and outputs. This remains true even if noise* *affects the spikes. This principle can be extended even to innovative applications such as the integration of biosensor technology with classroom teaching of English. Biosensors could measure cognitive responses like engagement and stress levels through the SNN. These can adjust teaching strategies dynamically, offering personalized and effective learning environments. It is thus necessary to show that the piecewise linear gain function of the sigmoid neurons can be incorporated into the spiking framework based on spike timing approximations of analog functions with precision.*

**Theorem 2:** *It is possible to use ordinary feed-forward networks with a single hidden layer to approximate any measurable function to any desired level of precision and to uniformly estimate any continuous function on any compact set. Therefore, the following corollary is implied by Theorems 1 and 2 together. Moreover, the integration of biosensor technology into English classroom teaching can offer new approaches to monitoring and improving learning, thus opening up new possibilities for personalizing educational approaches and measuring engagement in real time. Approximate any given continuous function* $F: [0,1]^n \rightarrow [0,1]^m$ *arbitrarily closely, according to Corollary 1. This principle can be applied in different domains, including English classroom teaching based on biosensor technology, where SNNs could be used to model and analyze temporal patterns in physiological data. This would allow for personalized feedback mechanisms, adjusting teaching strategies to the dynamic emotional and cognitive states of students.*

English classroom teaching through biosensor technology, SNNs can integrate into English classroom teaching and provide a disruptive way to improve learning outcomes. Biosensors can monitor such physiological states as stress and emotional arousal levels to give instant feedback to instructors about a student's cognitive state. SNN can analyze this biosensor data and provide actionable insights that could be used to tailor teaching strategies in response. With these technologies in place, educators can work toward providing personalized learning experiences for their students, creating an environment of higher engagement and retention. This innovative approach is not only modernizing the teaching of English but also bridges the gap between old methods of teaching and modern neuroscience-driven techniques.

## 4. Result

The integration of biosensor technology with SNNs increased the interest of students, removed learning anxiety, and improved the efficiency of learning in English language classrooms. The physiological information regarding the cognitive states of students acquired through biosensors was used to get insights into their cognitive and emotional states for dynamic adjustment of teaching strategies. Through this personalized learning approach, measurable improvements in participation reduced anxiety levels, and higher retention rates compared to the traditional methods indicate the effectiveness of the proposed system. The system is powered by an Intel 16 GB of DDR4 RAM, an Xeon E3-1230v5 CPU, and an

NVIDIA Quadro K420 discrete graphics card. It also has a 1TB SSD, guaranteeing express and successful storage.

- Week 1 Evaluation of Interactive English Classroom Teaching

In the first week of interactive English classroom teaching with the biosensor technology, several parameters were measured to determine the effectiveness of this method. The analysis helps to influence the student performance learning under a biosensor learning environment. The student engagement was at 7%, which is a representation of the participation of students in the learning process. The cognitive load was measured at 5%, which is the depiction of the mental effort that students needed. The task completion efficiency was at 4%, which indicates how quickly students completed the assignments. Attention focus was one of the factors at 6%, showing the level of students focused in class. Teacher-student interaction was also taken into consideration, which contributed 5% to the total results, focusing on the balance between teachers and learners in this biosensor-enhanced system. These factors combined with additional information to stakeholders for students' emotional and cognitive disposition enable the appropriate interventions to boost engagement, minimize anxiety, and increase the student's learning achievement. **Figure 3** and **Table 1** illustrate the Week 1 Analysis of educational performance factors.

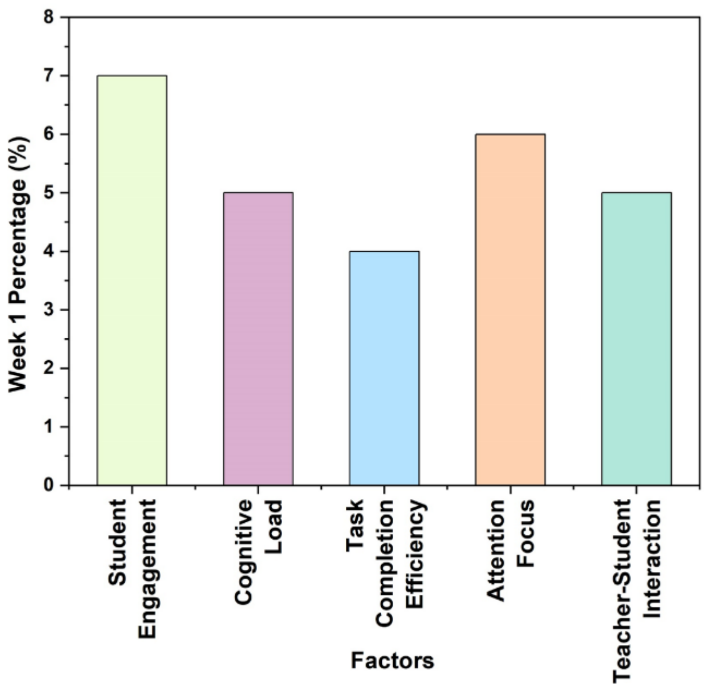


**Figure 3.** Result of Week 1 analysis of educational performance factors.

**Table 1.** Week 1 analysis of educational performance factors.

| **Factors** | **Week 1 Percentage (%)** |
| --- | --- |
| Student Engagement | 7 |
| Cognitive Load | 5 |
| Task Completion Efficiency | 4 |
| Attention Focus | 6 |
| Teacher-Student Interaction | 5 |

● Week 2 Evaluation of Interactive English Classroom Teaching

During the second week of the interactive English classroom teaching based on biosensor technology, several factors were gauged to evaluate how the technology was impacting students' learning experiences. The analysis findings show the effects of different factors on student performance in a technology-integrated classroom. Student participation stood at 12% proving that students were very active in the learning process. The cognitive load, recorded at 2%, demonstrated that the students were not overloaded with a mental burden that would entail high levels of learning complexity. Task completion efficiency was scored at 10%, a measure of how students were doing in completing their tasks. Focus on attention, which has been a requirement for learning, scored the highest at 14%, therefore meaning it is something that keeps students on track. Finally, there was teacher-student interaction which was rated at 12%; the analysis showed that the interactions arising from the use of the technology assisted the exchange of information between the teacher and students to enhance learning. **Figure 4** and **Table 2** represent the Week 2 Analysis of educational performance factors.

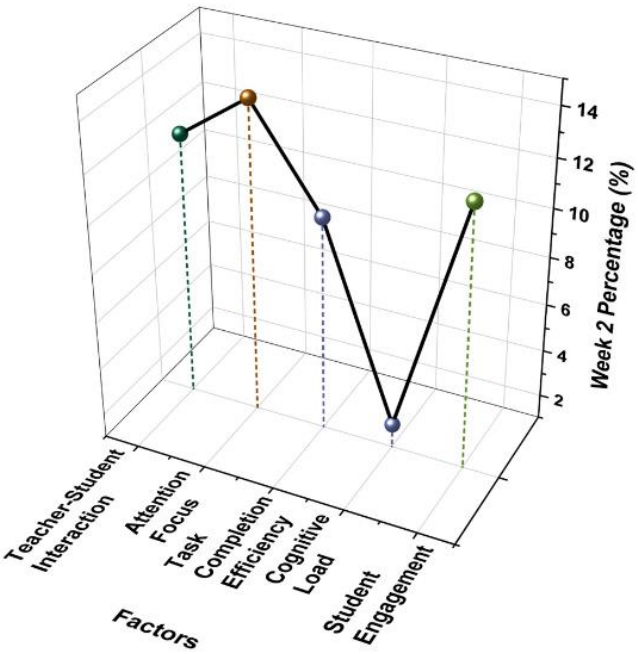


**Figure 4.** Result of Week 2 analysis of educational performance factors.

**Table 2.** Week 2 analysis of educational performance factors.

| Factors | Week 2 Percentage (%) |
|---|---|
| Student Engagement | 12 |
| Cognitive Load | 2 |
| Task Completion Efficiency | 10 |
| Attention Focus | 14 |
| Teacher-Student Interaction | 12 |

● Week 3 Evaluation of Interactive English Classroom Teaching

During the third week of the interactive English classroom education utilizing biosensor technology, factors affecting the learning environment were assessed. Student engagement accounted for 18% of the evaluation, underlining the importance of active participation in the learning process. The Cognitive load that attributed to 8% and assessed the difficulties faced by students with respect to their capacity to understand lessons. This moderate type of CLT index indicates that the technology introduced in the classroom did not impose much load on students. The 15% efficiency in completing tasks measured how effectively students worked to complete their tasks on time. The largest proportion is the attention focus, which was valued at 20% and indicated the student's capacity to concentrate during a lesson. Focus is key to achieving learning objectives and this score shows that, with the help of technology the students were able to stay focused. Lastly, teacher-student interaction which comprised 20% focused on the nature and the extent of communication that the teacher had with students due to the use of the technology to support learning. All these factors together provided a whole view of the student's learning process. **Figure 5** and **Table 3** depict the Week 3 Analysis of educational performance factors.

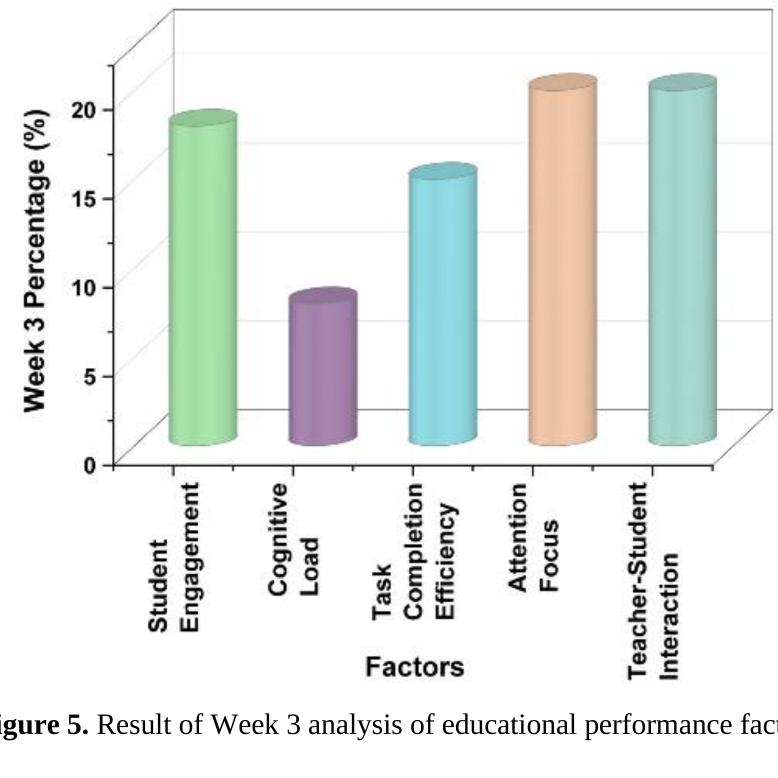


**Figure 5.** Result of Week 3 analysis of educational performance factors.

**Table 3.** Week 3 analysis of educational performance factors.

| **Factors** | **Week 3 Percentage (%)** |
| --- | --- |
| Student Engagement | 18 |
| Cognitive Load | 8 |
| Task Completion Efficiency | 15 |
| Attention Focus | 20 |
| Teacher-Student Interaction | 20 |

- Week 4 Evaluation of Interactive English Classroom Teaching

For grading the students, certain factors were considered in Week 4 focusing more on engagement, mental effort, and performance of the tasks. Student engagement was the most significant one, weighing at 30%. Learning activities have 10%, involved the estimation of the mental load of the tasks given to students and their level of difficulty. Task completion efficiency, which also contributed 30%, assessed to what extent the students completed the tasks on time. It demonstrated the capacity of the students in terms of organization and human relations in a particular lesson. Probably, the most important detail was attention focus which was weighted 35% recognizing the role of concentration during learning activities. Lastly, the teacher-student interaction was an aspect of WebDriver and was weighted at 35%, to stress the importance of good communication and support between the teacher and students. Principally, positive interactions affiliated with lending concepts, offer directions to obtain the student's performances. **Figure 6** and **Table 4** illustrates the Week 4 Analysis of educational performance factors.

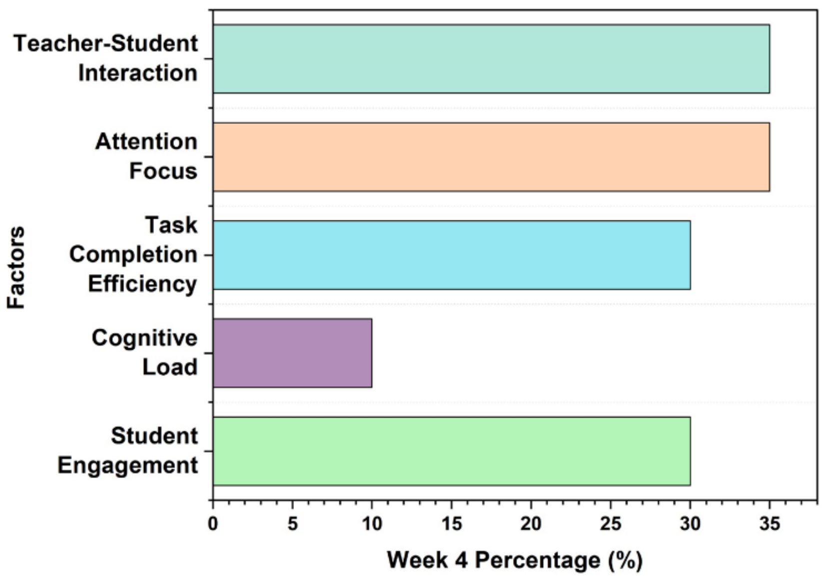


**Figure 6.** Result of Week 4 analysis of educational performance factors.

**Table 4.** Week 4 analysis of educational performance factors.

| **Factors** | **Week 4 Percentage (%)** |
|---|---|
| Student Engagement | 30 |
| Cognitive Load | 10 |
| Task Completion Efficiency | 30 |
| Attention Focus | 35 |
| Teacher-Student Interaction | 35 |

- ROC and AUC

The incorporation of biosensor technology in the teaching of English, therefore using novel methods for measuring engagement as well as cognitive responses by the students. Biosensors comprise EEG devices and heart monitors, which measure physiological signals related to attention levels, emotional states, and load of cognition in learning events. These data can then be evaluated in terms of measurement accuracy using ROC and AUC metrics. The curves drawn for ROC will enable the estimation of the sensitivity and specificity of biosensor reading signals for distinguishing between the cases of engaged versus disengaged learners. Values AUC gives a numerical characterization of the model performance. This method ensures that alterations in teaching styles based on data will result in enhancements in student engagement and further learning achievement in an English classroom. **Figure 7** demonstrates the findings of the ROC and curve AUC.

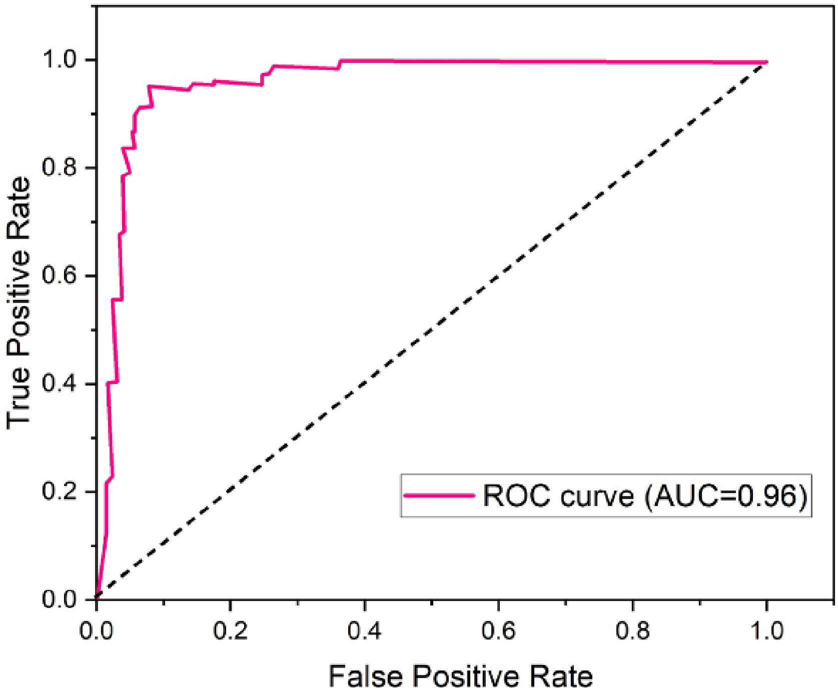


**Figure 7.** Analysis of ROC and AUC.

## 5. Discussion

The application of biosensor technology in the English language classroom can change the way that engagement and emotions are understood and addressed. Traditionally, educators have relied primarily on indirect measures, including test scores and surveys, to determine students' engagement or anxiety, which cannot give direct insight into their cognitive process. This research introduces a more direct and continuous method of assessment through the use of biosensors that monitor physiological signals such as heart rate variability, eye movement, facial expressions, posture, and seating data. Real-time measures reflect the learner's emotional and cognitive states more accurately and permit instructors to adjust teaching strategies to individual needs dynamically. The use of SNNs takes it to a higher level as this approach simulates the way the brain processes its neurons, thus allowing the system to adjust content according to the physiological responses of the students. This is crucial in personalized learning, as instructional materials are adjusted for students to stay interested or help minimize anxiety levels in a language learning environment. This is the most typical hindrance to making further progress.

The findings prove that there exists many possibilities through using the integration of biosensor technology along with more advanced neural network models to ensure higher engagement rates, lesser anxiety, and greater overall learning efficiency for students. SNN and biosensor technology were used to elevate the new degree of complexity. The system could evaluate physiological data and dynamically modify the speed and substance of teaching since SNNs simulate how the human brain processes information. Educational experience might be achieved by educators through utilizing real-time data to create an atmosphere with sympathetic and sensitive to students' needs. A paradigm shift in education, driven by biosensors and SNNs, provides a more responsible and individualized learning experience, making teaching more responsive, data-driven, more attuned to the student's emotional and cognitive needs, and these can be stretched into other fields, whereby the process's success depends more on a student's engagement and emotional handling of the process.

## 6. Conclusion

The integration of the biosensor technology with SNNs into English language classrooms results in a stress reduction, and enhancement in the participation of students and learning effectiveness during the four weeks' duration. They monitored and analyzed physiological data, including heart rate variability, eye movement, facial expressions, posture, and seating preferences, to assess the real-time cognitive and emotional states of students and thereby enable adaptive teaching strategies to be applied by individual needs. Noise reduction and normalization techniques ensured the accuracy and clarity of the collected data, thus enhancing the overall effectiveness of the biosensor system. Over the four weeks, the recorded progressive enhancement in the engagement of the students, efficiency in the completion of tasks, attention focus, and interaction between the teachers and the students. In week one, the engagement, as well as the cognitive load were low, but this improved in subsequent weeks and was much more evident by Week 4. The breakdown is as follows: Student engagement (30%), cognitive load (10%), task completion efficiency (30%), attention focus (35%), and teacher-student interaction (35%). The technology also demonstrated the effective reduction of cognitive load as it adjusted the difficulty and pacing of lessons based on real-time feedback, thus preventing students from feeling inundated.

### Limitations and Future Scope

The findings have underscored the potential that biosensor technology and SNNs hold in changing interactive language learning by providing instructors with tools for responding promptly to the needs of students. To enhance both the efficiency and enjoyment of the learning process. Future research should explore the scalability of this system in diverse educational contexts and its applicability across different subjects outside of language learning.

**Ethical approval:** Not applicable.

**Conflict of interest:** The author declares no conflict of interest.

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