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Enhancing Cognitive Performance of College Students Based on Adam Optimization Assisted by Brain Biofeedback

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Abstract

College students often face obstacles in achieving optimal cognitive performance due to the demands of academic stress during workload and the side effects of cutting-edge media that destroy the students' attention and cognitive skills. This study aimed to investigate the effectiveness of the adaptive moment estimation (Adam), an optimization algorithm designed for training deep learning (DL) models, assisted with brain biofeedback to enhance students' brain synapse transportation by boosting the cognitive performance of college students. The contribution of the study is to improve the academic cognitive skills of college students by processing input data (text, and videos). The study used an electroencephalogram (EEG) headset to read attention signals as brain biofeedback combined with the Adam optimization algorithm that trained on the student attention dataset to improve cognitive performance parameters. Adam's optimization algorithm represents the suggested deep learning model. Results improved the attention accuracy (97.51%), mental fatigue and drowsiness (3%), and precision at predicting learning performance improved by (20%) for college students trained on the Adam optimization algorithm-assisted brain biofeedback system compared with state-of-the-art models concerning the same attention dataset. The study provides evidence that combining Adam and brain biofeedback effectively boosts college students' performance, cognitive skills and synapse transportation system.

Keywords: Adam Optimization Algorithm, Brain Biofeedback, Cognitive Performance of College Students, Deep Learning, Electroencephalogram.

1 Introduction

Improving the cognitive performance of college students became the target of developed societies to achieve academic success. Where impaired attentional control represents one of the major factors leading to decreased individual academic behavior which requires continuous focusing (Du et al., 2022). To achieve optimal attention levels, the researchers studied strategies to detect and monitor the attention biofeedback signals of student's brains (Zeng et al., 2021). This enhancement can be established by

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performance observation during the specific task execution and the percentage of optimized attention, short-term memory, and problem-solving skills in college students (Ma et al., 2023; Biswas, 2024). One of the promising tools for observing and detecting the cognitive mental state and real-time attention activity of college students is EEG tools. The EEG tools can measure the brain biofeedback and provide information about attention levels and relevant factors (Ramírez-Moreno et al., 2021). The collected EEG data on attention level can be compared with an ideal dataset of attention level. The computer vision (CV) and DL methods can solve the accuracy issue of classification and detection of the EEG signals to reach the optimal level of attention signals (Espino-Díaz et al., 2020). Cognitive overloading is the main obstacle for many college students, which leads to decreased attention levels, impaired short-term memory, and reduced problem-solving capability for college students. Academic societies contributed in recent years to improving the focus of students by harnessing the artificial intelligence (AI) optimization method to enhance student focusing by improving the synapse system which is measured by EEG brain biofeedback. Some studies used EEG-based systems to work on ways to avoid failures caused by mental fatigue which leads to human mistakes through inter-subject transfer learning. Some other studies used wearable systems based on EEG to predict student cognitive and emotional engagement through automated and adaptable teaching platforms (Apicella et al., 2022). Another study classified the cognitive workload utilizing EEG-based and DL techniques (Gupta et al., 2021). Some studies predict the cognitive performance of university students inside the classroom utilizing neuro engineering-based DL tools. Regarding students' learning and cognitive engagements in virtual classrooms during the pandemic period, some studies present EEG-based microcontroller systems to keep students engaged through learning procedures (Arvinth, 2024). Some other studies focused on EEG-based regression methods to create models to detect fatigue ratio in tasks requiring continuous concentration. Convolutional networks are also used to detect human fatigue depending on facial emotion. Some other studies used Raw EEG and DL to identify the real-time learning period for students (Abbasi et al., 2024; Mannonov et al., 2025). Some other studies used eye blanking and brain activity to measure the cognitive performance of students (Jamil et al., 2023). The contribution of this study is to create a wearable system using the Adam optimization algorithm driven with EEG brain biofeedback to enhance student focusing through the classroom.

Table 1: The abbreviation description

Term	Description
Adam	Adaptive moment estimation
AI	Artificial intelligent
BCI	Brain-computer interface
CV	Computer vision
DL	Deep learning
EEG	Electroencephalogram
GAF	Grampian angular field
GA-CNN	Graph-based conventional neural network
LSTM-CNN	Long short-term memory - conventional neural network
MSE	Mean squared error

The study hypothesis is that it can improve student focus by enhancing the student synapse system and attention level which can measured and rectified by an EEG headset and Adam algorithm after applying to the student several tasks to complete (reading texts and watching videos then answering some questions). The sections of this study are organized as follows. Section 2 illustrates the prior studies related to the idea explained in this study. Section 3 shows the preliminaries, fundamentals,

methodology, data acquisition, and benchmarks. Section 4 displays the results discussed in Section5. The conclusion is the last section. Table 1 shows the short terms in this study.

2 Prior Studies

The strategy of using DL techniques supported with brain biofeedback promises a sophisticated and meaningful education in today's societies (Abadi & Elbaz, 2023; Bakhronova et al., 2025). EEG brain biofeedback is used to get brain activity (attention band) after analysis of the data. Whether optimization techniques (like Adam optimizer) can classify emotional responses and levels of student engagement. This section illustrates the prior studies about using EEG-based computer vision to improve human attention and reduce fatigue. Effectively utilizing EEG attention bands to detect focus levels for students during education procedures including with LSTM, RNN, and CNN has been achieved in some studies with accuracy reaching 96% in general (Al-Nafjan & Aldayel, 2022; Verma & Kulkarnin, 2025). Other researchers used DDQN networks to measure student engagement (Kaushik et al., 2022; Shaw et al., 2023). Also, another study improved CNN by using a hybrid CNN-Transformer model based on EEG signals biofeedback with an accuracy equal to 90.13% in general (Pathak & Kashyap, 2023). Some other studies used an Extreme machine learning model to detect confusion and cognitive load for students. Some studies applied GAF encoding techniques on EEG data to predict mental states achieving 83% accuracy in detecting confusion (Gupta et al., 2024). There are some studies that show evidence that shallow learning is better than deep learning after applying their research on predicting the cognitive performance of 127 students (Zhou et al., 2021). There are some developed models that integrate DL with psychological frameworks, for instance, the Russel2D model to achieve improved emotion recognition (Sukumaran & Manoharan, 2023). Some studies used the LSTM-CNN model to improve learning with accuracy equal to 94% for college students. There is other hybrid models developed like GN-CNN to address the challenges of EEG noise in detecting the best attention band for college students. Critical moments of confusion during online learning and allowing teachers to provide timely support utilizing the DL model have been studied. Table 2 summarizes the prior studies.

Table 2: The Analysis of Prior Studies

Strategy	Model type	Accuracy (%)	Reference
Detecting Attention	LSTM CNN	96	(Al-Nafjan & Aldayel, 2022; Kaushik et al., 2022; Shaw et al., 2023)
Identifying Confusion and Cognitive Load	Extreme Gradient Boosting	83	(Gupta et al., 2024)
Hybrid Models	GA-CNN	95.69	(Avital et al., 2024)
Personalized Learning Systems	TSMG Model	87	(Men & Li, 2022)

3 Preliminaries

The preliminaries section describes the methodology followed in this research. The section explains the proposed EEG-based attention recognition system for college students. The first part explains the proposed scheme, with the attention detection and classification algorithm for optimization and data gathering strategy. The mathematical complexity, benchmarks used in this research, mind feedback signal processing, feature extraction, and attention computation stages, have been clarified.

Proposed Framework Architecture

The framework architecture in Figure 1 illustrates the strategy used in the proposed study. The system gathers attention signals as brain biofeedback, which comes from each task implemented by students. The tools used to gather attention signals by the Brain-Computer Interface (BCI) headset. The EEG signals come from BCI, to estimate attention and train the data, utilizing the Adam optimization algorithm to classify optimal attention signals.

The image illustrates a schematic diagram of a BCI utilizing EEG data for attention analysis. The system operates through several stages, which are outlined below:

1. Input Sources: The system begins with text and video inputs, which are processed by the user's cognitive functions.
2. BCI Headset: These cognitive signals are captured using a BCI headset, which acquires EEG signals from the user's brain.
3. Data Acquisition: The EEG signals are collected in the Attention EEG dataset, facilitated by the Open Vibe platform. This stage is critical for capturing precise brain activity relevant to attention tasks.
4. Data Processing: The acquired data undergoes processing using MATLAB, a computational software environment. This step involves filtering and preparing the data for feature extraction.
5. Feature Extraction: Features pertinent to attention analysis are extracted from the processed EEG data. This step is crucial for understanding specific patterns in the brain signals.
6. Adam Algorithm: The extracted features are then utilized by the Adam algorithm for further analysis or model training. This algorithm helps in optimizing the learning process by adjusting weights.
7. Feedback Mechanism: The final stage involves providing feedback, termed "Brain feedback," which likely refers to adjusting the system or providing real-time information to the user.

This diagram succinctly represents the complex interaction between cognitive inputs, EEG signal processing, and feedback mechanisms in a BCI system focused on attention analysis. The software integration tools like MATLAB and Open Vibe demonstrate the technological interplay required for successful implementation.

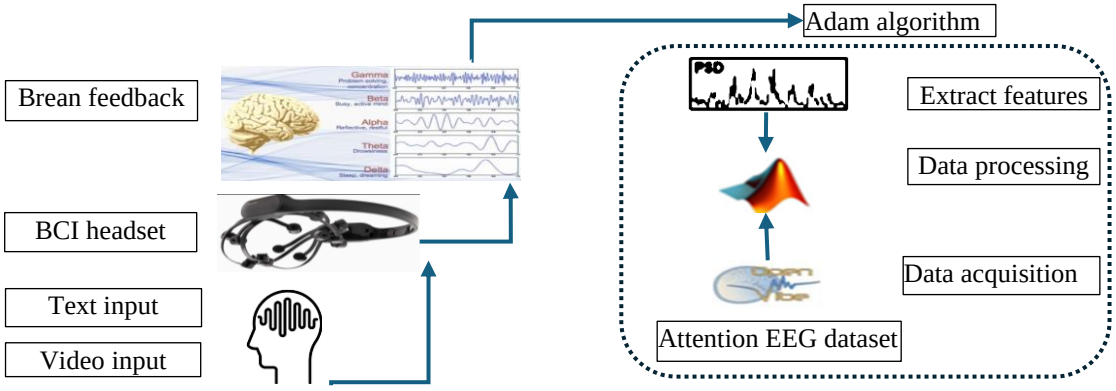


Figure 1: The proposed framework structure to enhance cognitive performance for college students utilize Adam optimization and brain biofeedback

The Enhanced synapse system procedure for college students based on Adam optimization and EEG brain feedback is shown in Algorithm 1.

Algorithm 1: Enhance synapses system procedure for college students based on Adam optimization and EEG brain feedback

Algorithm: Attention enhancement system for students.
Method: Adam optimization.
Input: learning material (Texts, Videos).
Output: improve college students' attention.
Procedure steps:
1. Start
2. Initialize $\theta 0$, $\propto$, m0, and $j(\theta 0)$
3. Present learning material to the college students.
4. Data acquisition
5. Data processing and EEG bands extraction.
6. Evaluate objective function and brain activity.
7. For loop Calculate gradients of attention level.
   Apply Adam optimizer:
   Update first momentum.
   Update second momentum.
   Calculate the bias correction first moment.
   Calculate the bias correction second moment.
   Update the attention signal.
   Update brain biofeedback.
8. Loop
9. End.

Adam Optimization in Enhancing Cognitive Performance

Adam's optimization algorithm is a short-term adaptive momentum estimation that follows the DL approach. The algorithm proposed to adjust attention parameters to achieve optimal focus for college students. The optimizer combines two well-known algorithms, Ada Grad and RSM Prop. In this study, the Ada Grad represents the new attention value with less noise, which comes from student brain biofeedback after seeing videos and text materials. On the other side, RSM Prop represents the attention processed with the learning rate results (Nguyen et al., 2021). Table 3 describes the mathematical equations, and method complexity can be divided into the following keys (Reyad et al., 2023).

Calculate gradients (attention signals): the system first needs to gather attention data with less noise ratio, as shown in Equation 1.

$$g_t = \nabla_{\theta_t} j(\theta_t) \quad (1)$$

Calculate the first momentum (attention average rate): the exponentially decaying average of the past attention signal, which represents the first momentum estimation can be calculated by using Equation 2.

$$m_t=\beta_1\ m_{t-1}+(1-\beta_1)g_t \quad (2)$$

Calculate the second momentum (attention squared average rate): to adapt the learning rate by calculating the squared average of exponentially decaying average utilizing Equation 3.

$$v_t=\beta_2\ v_{t-1}+(1-\beta_2)g_t^2 \quad (3)$$

Correction of bias: the bias correction is used to correct the attention ratio to be near to the idle attention ratio to enhance the student's focus. The bias correction equations for first and second momentum estimates are calculated by Equations 4, 5.

$$\hat{m}_t=\frac{m_t}{1-\beta_1^t} \quad (4)$$

$$\hat{v}_t=\frac{v_t}{1-\beta_2^t} \quad (5)$$

Update the parameters: in the end, the attention signals are optimized by updating the bias correction values for the first and second momentum estimates rate in Equation 6.

$$\theta_{t+1}=\theta_t-\propto\frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon} \quad (6)$$

Table 3: The description of parameters

Parameters	Describe
T	Current time step
gt	Gradient with respect to θt at the current time
J(θt)	Objective function at time step (t)
θt	Attention signal parameter per time (t)
mt	First momentum estimates at time (t)
m(t-1)	First momentum estimates at previous time
β1	Exponential decay ratio to the first momentum estimate ≈ 0.9
vt	Second momentum estimates at time (t)
v(t-1)	Second momentum estimates at previous time initialized with zero
β2	Exponential decay ratio to the second momentum estimate ≈ 0.999
mˆ_t, vˆ_t	Bias correction
θ(t+1)	The update of the attention signal for the next time (t)
∝	Learning rate
ϵ	Epsilon is added value to avoid divided on zero
Aimp	Attention improvement
Awith fb	Attention with brain biofeedback
A without fb	Attention without brain biofeedback
n	Time step samples
yˆ_i	Predicted attention level at time (i)
yi	Desired attention level at time (i)

Data Acquisitions

The purpose of using the student's attention detection dataset (Hossen & Uddin, 2023), is to compare the attention band that comes from a dataset with the data income from the EEG headset after being applied to a student through reading text and video materials tasks. Adam's optimization algorithm uses

the attention dataset and attention that comes from the EEG headset through the task period, for the learning and testing procedure of the training stage. When the system learns the best period and materials to enhance student attention, the system will supervise itself to predict the suitable period and material to improve student attention and focus.

Benchmarks

The baseline measure of the college students' understanding depends on students' attention level when engaging with the applied learning materials (text, and videos). The attention improves after applying the proposed method, as shown in calculated in Equation 7.

$$A_{imp.} = \frac{A_{with\ fb} - A_{without\ fb}}{A_{without\ fb}} \times 100\ \% \quad (7)$$

The proposed system predicts the best attention level for students simultaneously. The mean square error (MSE) shown in Equation 8 measures the difference between time step predicted attention and target attention level.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \quad (8)$$

The accuracy of students' attention values, which is shown in Equation 9, represents the relevant issue when talking about benchmarks. Through collecting attention values, some signals spend more time on specific values at that time and measure the accuracy is not enough. F-score, precision, and recall provide more nuanced observations than just accuracy. Equations 10-12 show the mathematical complexity of these factors.

$$Accuracy = \frac{\text{no. of correct prediction}}{\text{no. of prediction}} \quad (9)$$

$$F\text{-score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (10)$$

$$Recall = \frac{\text{True positives}}{\text{True positives False negatives}} \quad (11)$$

$$Precision = \frac{\text{True positives}}{\text{True positives False positives}} \quad (12)$$

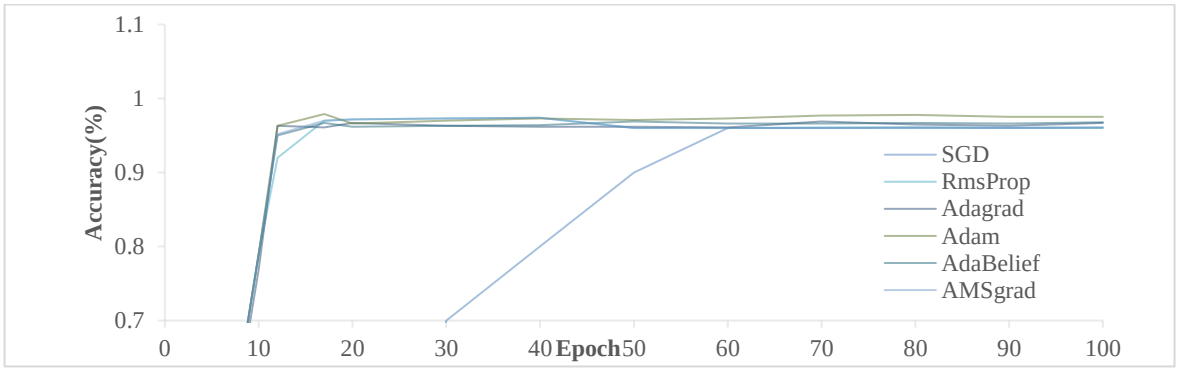
4 Results

Based on the implementation results, Table 4 illustrates how the proposed algorithm improves the students' attention. The results show the student synapse system after and before using the Adam optimization algorithm. The attention improvement metric shows a 25% efficiency enhancement in overall measured levels of attention compared with essential attention. Whither the highest average attention score reaches +0.14, which indicates that the students generally have a more attentive state throughout the learning session. The lower MSE error is -0.03, which means the predicted attention levels are more accurate. Increase the attention classification accuracy by 17% to better identify the attention of students. Recall, precision, and F1-score are increased as brain biofeedback to reduce the mistakes of identifying low attention as high. The faster time to reach peak attention is -45 sec. for students to reach high focus. The high attention duration reaches 7 min of focusing. The time spent through learning tasks reaches 7 min. The assessment score for improved learning outcomes reaches 15%. Figure 2(a) indicates the accuracy, and Figure 2(b) indicates the loss function. About the accuracy measuring, the comparison of Adam optimization with the state-of-the-art methods used in the same

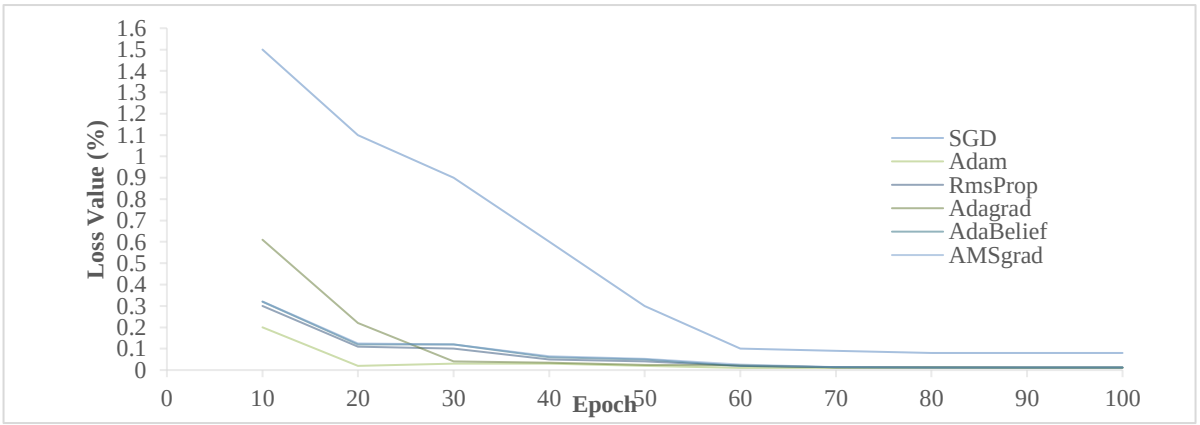
procedure (SGD (Basodi et al., 2020), Rms Prop (Lemhadri et al., 2021; Adagrad Arous et al., 2021), AdaBelief (Sheikhottayefe et al., 2025; AMSgrad; Chen et al., 2022) has been illustrated. From the results, the Adam optimization algorithm shows the best accuracy for student attention behavior compared with another algorithm with an average value close to 97.51% in general. On the other hand, the loss packets through the training procedure utilizing Adam optimization become 1.02% which is a lower loss compared to the other algorithms.

Table 4: Table of results across group of students after and before apply Adam algorithm

Metric curatoria	Before Adam algorithm	After Adam algorithm	Optimization
Attention improvement	N/A	N/A	+25%
Average attention score	0.55	0.69	+0.14%
MSE	0.08	0.05	-0.03%
Attention accuracy	65%	82%	+17%
Precision	55%	75%	+20%
Recall	60%	80%	+20%
F1-Score	0.57	0.77	+0.20%
Peak time attention	120	75	-45 sec.
Sustained high attention	8	15	+7 min.
Task time	25	32	+7 min.
Assessment	70%	85%	+15%



(a)

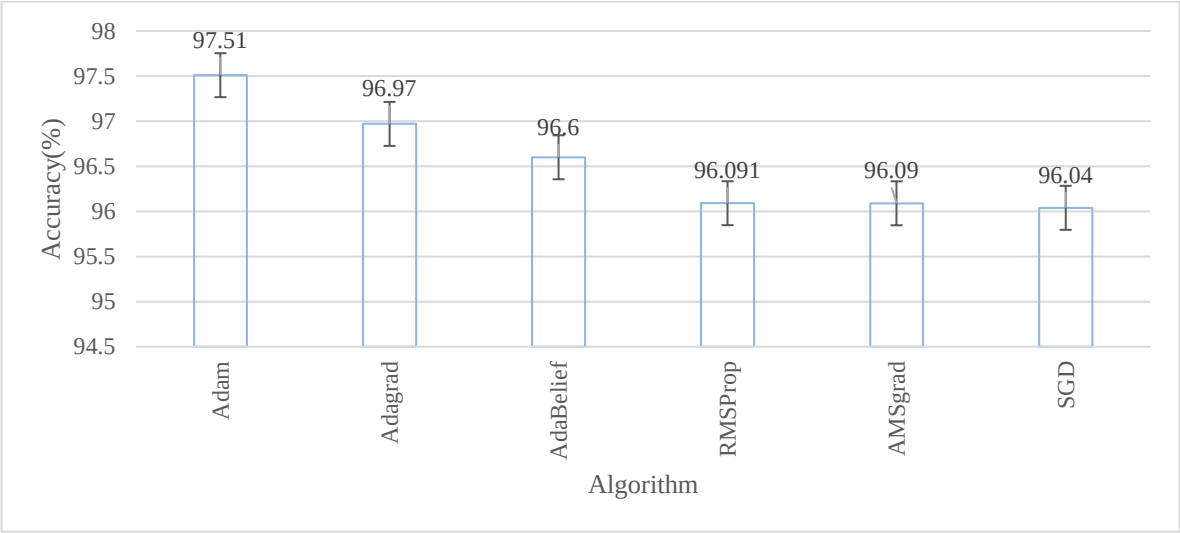


(b)

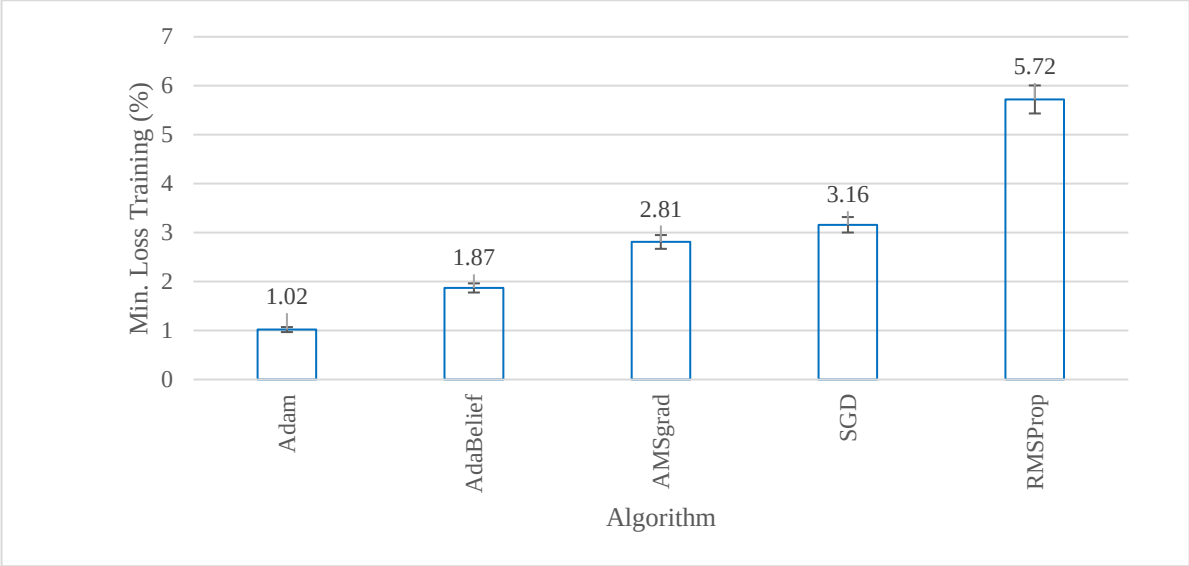
Figure 2: (a) Accuracy training of Adam optimizer method compared state-of-the-art, (b) Loss function during training procedure for Adam optimizer compared with state-of-the-art methods (SGD, Rms Prop, Adagrad, AdaBelief, AMSgrad)

5 Discussion

Figure 3 compares the behavior of Adam optimization with state-of-the-art optimization algorithms (Adagrad, AdaBelief, RmsProp, AMSgrad, and SGD). The Adam optimization algorithm shows the improvement of student attention across three key metrics: Accuracy, Minimum training loss, and iteration times to learn the system. From the observation in Figure 3 (a), Adam optimization achieves the best accuracy equal (97.51%) followed by Adagrad (96.97%), and AdaBelief (96.6%). While RmsProp, AMSgrad, and SGD show lower accuracies within the range of (96.04 ~ 96.09%). Figure 3(b) shows that Adam's optimization gets the lowest training loss with a value (1.02%). That indicates that it fits with the training dataset. The number of iterations required to reach a specific attention level is shown in Figure 3(c), where Adam optimization required 2721 iterations to reach the study state of the learning procedure. The results clearly show that utilizing Adam optimizer to robust attention for college students has been strongly supported in this study.



(a)



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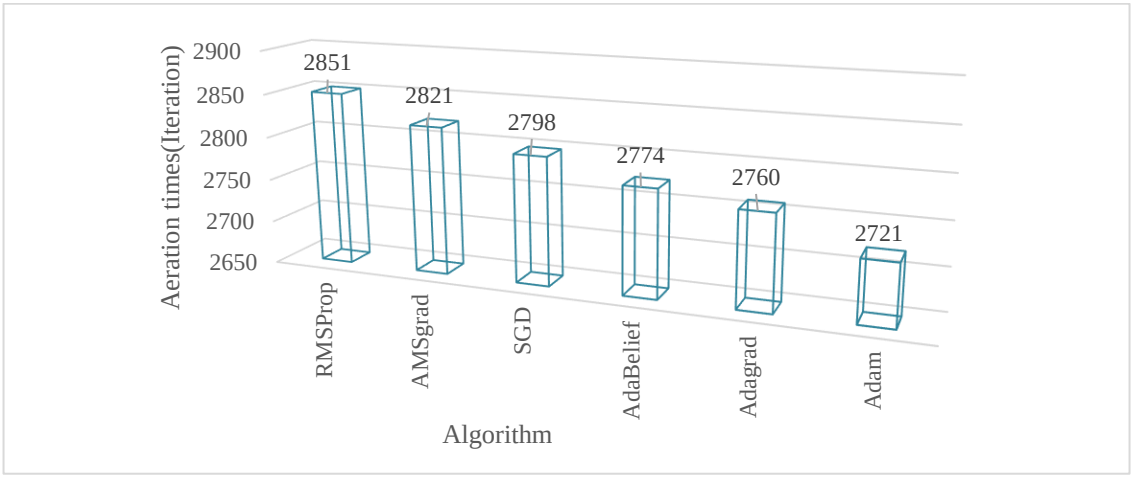

(c)

Figure 3: (a) The average accuracy for the compares algorithms, (B)The minimum loss function for the proposed algorithms, (C) Training iterations

Performance Comparison

The proposed method's performance compared with state-of-the-art methods declared in Figure 4. In presented in graph the highest accuracy of attention detection and processing goes to Adam method with 97.51 accuracy, while SGD reach to 96.04 accuracy. The high prediction F1-Score, and precision goes to RMSProp while the accuracy equals 96.09 percentage. The lowest measurements go to method AMSgrad and SGD respectively.

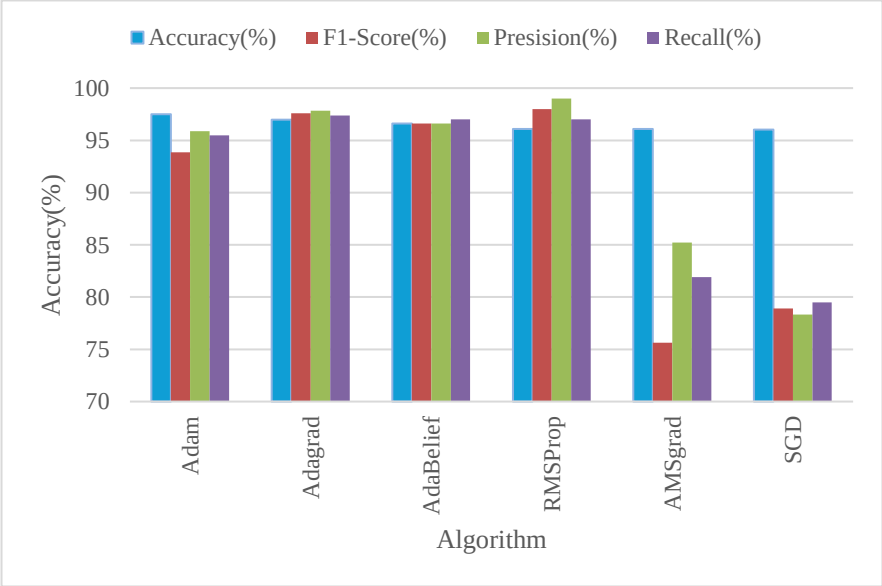

Figure 4: The performance comparison for the proposed method with state-of-the-art methods

limitation

The college student's attention enhancement suggested system, utilizing Adam optimizer with the aid of EEG brain biofeedback represents a cutting-edge strategy to improve AI education in developed societies. Although there are some obstacles considered as limitations in terms of long-term strategy.

EEG brain biofeedback signals come with interference noise which represents a key challenge when the attention band has been chosen. Lab tools are also one of the limitations through real-time implementation. The long-term effect is also a limitation issue to consider. Finally, the comfort of wearing the headset for students.

6 Conclusion

The study investigates the capability of enhancing college student attention and student synapse system, which is responsible for the focus aspect utilizing Adam optimizer as an algorithm that is boosted by brain biofeedback signals gathered by an EEG headset. The suggested system scheme and mathematical complexity of Adam's optimization algorithm have been illustrated in detail starting with calculating first and second moments, estimation, bias correction, and update parameters. The acquisition dataset to rectify the student attention with a nearly ideal attention band has been suggested and employed on MATLAB program to compose high performance. Several benchmarks (MSE, F1-score, Precision, and recall) have been introduced to measure student attention improvement where the Adam optimization algorithm achieved high accuracy, minimum training loss, and fast learning with fewer iterations. Study limitations have been also discussed from the side of noise, lab challenges, and the complexity of gathering the attention band. The study highlights the superiority of Adam's optimization compared with the other art-of-the-state methods.

Author Contribution

Conceptualization, Elaf Ayyed Jebur; methodology, Marwan Kadhim Mohammed AL-shammari; software, Mohammed Rajih Jassim; validation, Elaf Ayyed Jebur; formal analysis, Marwan Kadhim Mohammed AL-shammari; investigation, Mohammed Rajih Jassim; resources, data curation, writing—original draft preparation, Elaf Ayyed Jebur, Marwan Kadhim Mohammed Al-shammari, Mohammed Rajih Jassim.

Conflicts of Interest

The authors declare that there is no conflict of interest.

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