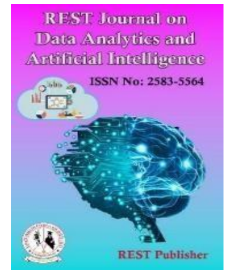
REST Journal on Data Analytics and Artificial Intelligence
Vol: 4(1), March 2025
REST Publisher; ISSN: 2583-5564
Website: http://restpublisher.com/journals/jdaai/
DOI: https://doi.org/10.46632/jdaai/4/1/11



BCI Game using EEG-based Emotion Recognition

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Abstract: *This project presents a gaming system that utilizes brain-computer interface (BCI) technology to detect players' emotions in real-time using electroencephalography (EEG) signals. The game adjusts its difficulty level based on the player's emotional state, creating a unique and truly immersive experience. By integrating machine learning algorithms with EEG data, our system enables a new dimension of human-computer interaction, where players' emotional states dynamically influence the gaming experience. This BCI approach aims to enhance player engagement, immersion, and emotional investment in games, while also providing insights into the emotional responses of players. This innovative system contributes to the development of affective computing in gaming, demonstrating the vast potential for EEG-based emotion recognition to revolutionize the gaming industry.*

Keywords: *Brain-Computer interface, Electroencephalography, real-time, human-computer interaction, machine learning.*

1. INTRODUCTION

What is BCI? BCI stands for Brain-Computer Interface which refers to a direct communication pathway between the brain's neural activity and an external device, usually a computer or machine. BCIs are designed to translate brain signals into commands or actions enabling users to control devices purely through thought without physical movement [1-5]. Brain-Computer Interface (BCI) combines two fundamental research areas: Neuroscience and Human-Computer Interaction (HCI) that serve as a link bridge that allows users to interact with the computer based on commands transmitted directly from the brain to the standard input of the computer BCI systems use different neuroimaging sensors to retrieve evoked brain signals through a specific thinking process that corresponds to a certain mental state of the user at a time that can be converted into a computer command [6-8]. To provide a general overview of sensory, motor and cognitive processes, the BCI system uses the electroencephalogram (EEG) principle to measure electrical activity of the brain, which is diffusely distributed across the scalp and that corresponds to the brainwaves alpha, beta and theta. BCI is still a cutting-edge technology [7]. With the development of relevant theories, experience accumulation and in-depth technical research, it will be applied to more fields that mainly include medical healthcare, military, education and training, game entertainment, aerospace, smart home, etc. [9-10].

How BCIs Work: BCIs first acquire brain signals, which are electrical impulses produced by neurons firing in the brain, which is known as Signal Acquisition. Depending on how close electrodes get to brain tissue, current implementations of BCIs range from non-invasive and partially invasive to invasive [11-12]. "Invasive" BCI generally refers to the surgical implantation of signal acquisition electrodes into the gray matter of the brain, which allows high-quality EEG signal acquisition and more accurate and immediate external device control [13]. Due to the need for complex implantation procedures, which may easily trigger immune responses, tissue damage and signal attenuation, "invasive" BCIs are currently still in the human trial stage [14-15]. "Non-invasive" BCI refers to the placement of signal acquisition electrodes directly outside the skull to collect neural information. By eliminating the need for surgical intervention, this method has advantages in terms of safety and convenience of disassembly and assembly [16]. The "partially invasive" BCI refers to the implantation of signal acquisition electrodes between the cranial cavity and gray matter for information analysis mainly based on cortical electroencephalogram (EEG). In terms of signal acquisition quality and safety, this method is in the middle of the other two technologies [17].

FIGURE 1. Bit brain dry EEG and a Muse Head Band

A device called EEG (Electroencephalography) is used to capture the signals from the brain. Electroencephalography (EEG) is a non-invasive method used to record the electrical activity of the brain [18]. It captures brainwave patterns through electrodes placed on the scalp. These electrical signals are produced by the firing of neurons in the brain and can be measured in real time, providing valuable insight into brain function.

How BCI Works in Gaming: Brain-Computer Interface (BCI) technology is being explored in gaming to create more immersive and interactive experiences, allowing players to control in-game actions using only their brain activity. This new approach to gaming replaces or complements traditional control methods (like keyboards, controllers, or motion sensors) by interpreting a player's brainwaves to directly influence gameplay. BCIs for gaming are typically non-invasive, using technologies like EEG (Electroencephalography) to measure brain signals [19]. The player wears an EEG headset or cap that has electrodes attached to the scalp. These electrodes detect the electrical activity of the brain. The headset is wirelessly connected to a computer or gaming console that processes these signals. The brain signals are processed in real-time to extract specific patterns related to the player's mental state or intentions, such as focusing, relaxing. Using machine learning algorithms, the BCI system interprets these patterns to generate commands that the game can understand. Some games measure the player's mental state (e.g., relaxation, focus, stress). These signals can be used to change the environment or gameplay dynamics. For instance, certain horror games may increase difficulty or intensity based on the player's fear levels. Mind-controlled meditation games are designed to help players relax. The game may progress, or change based on how well the player calms their mind.

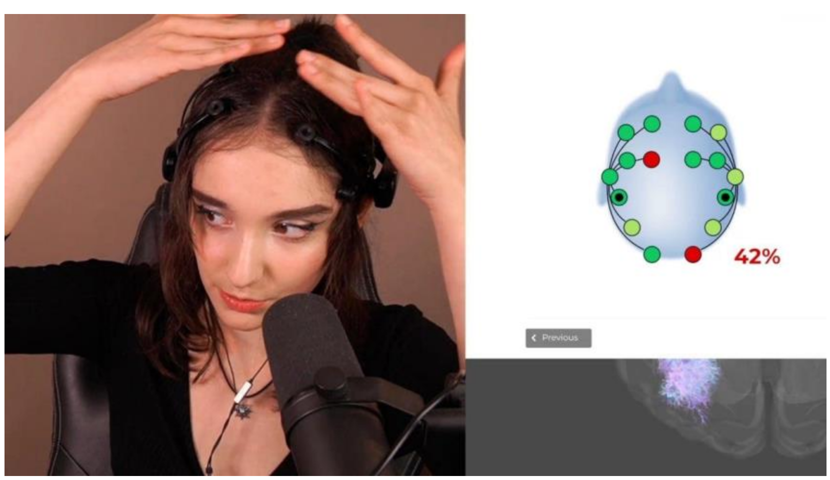

FIGURE 2. Twitch Streamer tries BCI

Emotion Recognition: Emotion Recognition in gaming involves using brain-computer interfaces (BCIs) to detect a player's emotional state and applying that data to influence or modify the gaming experience. By interpreting brainwave patterns or other physiological signals, the game can dynamically adjust its gameplay, environment, or difficulty based on the player's emotional reactions, making the experience more interactive and immersive. For example, when the player is excited, the game increases the difficulty level or introduces new challenges IF the player is frustrated, the game offers hints or reduces the difficulty level. Or when the player is relaxed, the game rewards them with bonus points or power-ups. EEG headsets would detect electrical activity in the brain. Different emotional states (e.g., excitement, fear, frustration) produce unique brainwave patterns, and these patterns can be classified into emotional categories using machine learning algorithms.

2. METHODOLOGY

EEG (Electroencephalography) Sensors: EEG headsets are equipped with sensors that detect electrical activity in the brain. Different emotional states (e.g., excitement, fear, frustration) produce unique brainwave patterns, and these patterns can be classified into emotional categories using machine learning algorithms. This EEG data is processed in real-time to identify specific emotional indicators such as focus, relaxation, stress, excitement, or frustration. Some systems may combine EEG with other physiological data, like heart rate (HRV), skin conductance (GSR), or eye movement, to enhance the accuracy of emotion recognition.

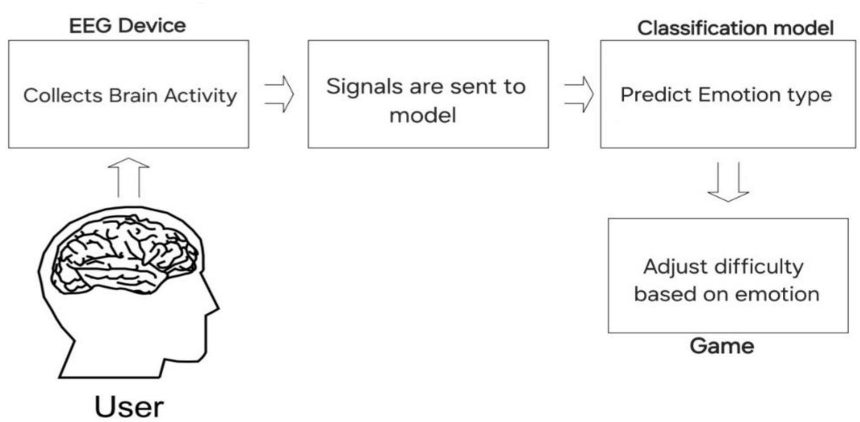

FIGURE 3. Emotion Recognition in gaming

Emotion Classification: The processed data is fed into machine learning models that classify the player's emotional state into categories like calm, excited, fearful, anxious, frustrated or simply positive, neutral and negative. These classifiers can detect transitions between emotional states, allowing the game to respond to the player's emotions dynamically. Different machine learning or deep learning algorithms like Decision Tree, Random Forest, Recurrent Neural Networks, and Support Vector Machines can be utilized for training the classification model.

Game Difficulty: The model's predicted emotion type will be sent to the game and the game would adjust its difficulty or mechanics. The game can dynamically adjust its gameplay, environment, or difficulty based on the player's emotional reactions. This will enhance player engagement, immersion, and emotional investment in games, while also providing insights into the emotional responses of players.

3. IMPLEMENTATION

Technology Used: The implementation of the proposed system relies on various technologies and frameworks to ensure efficient development, execution, and performance of the EEG device and the game.

The following technologies are utilized: programming language: Python facilitated the development of the project through its extensive libraries and simple syntax, enabling efficient EEG data processing, emotion recognition, and game development. Python's vast community and resources ensured easy integration of machine learning and game development components.

Development Environment: Visual Studio Code (VS Code) provided an ideal environment for developing the project in Python. Its intuitive interface, syntax highlighting, and code completion features enabled efficient coding. Seamless integration with Python libraries and frameworks, streamlining project development.

Game Development library: Pygame provided a simple, fast and efficient game development framework for the EEG-based emotion-aware game project. It’s easy-to-use modular design enabled rapid prototyping and development of the game mechanics, seamlessly integrating with Python's EEG data processing and machine learning capabilities.

EEG Library: PyEEG, a Python library for EEG signal processing, enabled efficient extraction of relevant features from EEG data in the emotion-aware game project. Its intuitive built-in algorithms simplified EEG data analysis.

Machine Learning Library: Scikit-learn provided robust classification algorithms for emotion recognition in the EEG-based game project. Random Forest and Decision Tree classifiers were utilized to accurately classify EEG-derived features into distinct emotional states. These algorithms' high performance and interpretability enabled effective emotion recognition.

4. PROCEDURE

Dataset Description: The EEG data was collected from two people (1 male, 1 female), which was recorded using a commercial MUSE EEG headband of with a resolution of four (TP9, AF7, AF8, TP10) electrodes. Positive and negative emotional states are invoked using film clips with an obvious valence, and neutral resting data is also recorded with no stimuli involved, all for one minute per session. With a variable frequency resampled to 150Hz, this resulted in a dataset of 324,000 data points collected from the waves produced by the brain. Statistical extraction of the alpha, beta, theta, delta and gamma brainwaves is performed to generate this large dataset. This dataset suits best for broadly classifying the human emotions into three categories and use it for training the prediction model using machine learning algorithms.

Model Training: The machine learning prediction model was trained using the Random Forest classification algorithm implemented with Scikit-Learn. The training dataset consisted of EEG data collected from participants, labeled with corresponding emotional states (positive, negative, and neutral). The trained model achieved an accuracy of 99.218% on the test dataset, demonstrating its effectiveness in classifying emotions based on EEG data. Decision Tree Classifier was also tested which resulted in an accuracy of 96.093%. Since the performance of the Random Forest classifier was better, it has been selected for more accurate results while the model is working real-time. The model was then exported using joblib for integration with the PyGame application. The model's performance was also evaluated using metrics such as precision, recall, and F1-score.

Game Development: Any game, a newly developed or an existing one can be used in this. To develop a new game, Unity3D engine, Steam, Lightening Studio or the Pygame library provide various tools for implementing GUI or other game mechanics. Here, PyGame was used to design a simple Dinosaur that is very similar to the Chrome Dinosaur game but with colors. This simple game features a dinosaur running endlessly across a desert landscape, where players control jumps and crouch to avoid obstacles like cacti and birds. The game speeds up as progress is made, ending upon collision. Notable features of this include basic graphics, increasing difficulty, score tracking, and no internet requirement.

Integration and Communication: The integration and communication components enable seamless interaction between the EEG device, machine learning model, and PyGame application. The EEG device streams brain activity data to the system with the help of PyEEG library, which is then fed into the trained machine learning model for emotion classification. The predicted emotions are subsequently transmitted to the PyGame application, adjusting game difficulty in real-time. In the dinosaur game, the speed of the dino will be taking effect. If the emotion is positive, then the speed would increase by a big number, if the emotion is neutral then the speed would increase by a small number and if it's a negative emotion then the current speed would decrease. This integrated system enables a dynamic gaming experience, adapting to players' emotional states.

5. RESULTS

Outputs: The following figure is the visualization of the wave form of a negative emotion EEG reading plotted during the training phase by using the python's matplotlib.pyplot library plot() function.

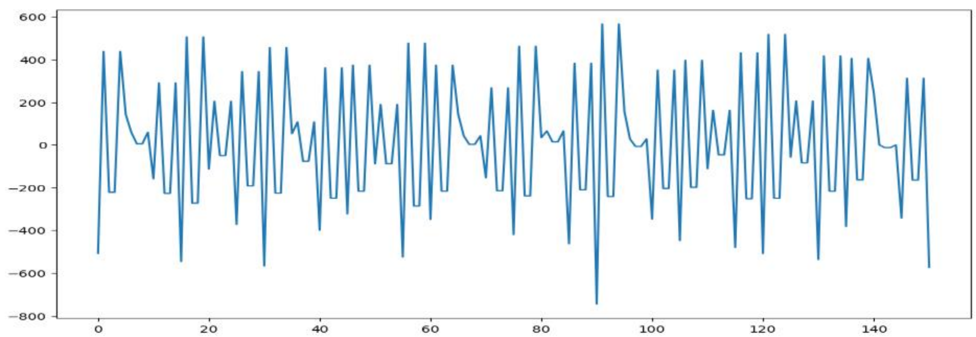

FIGURE 4. Plot of a Negative emotion EEG reading

Here is a screenshot of the pygame window while the game is in motion and the Dino is in action, ready to adjust its speed based on player's emotion. We can also see a cactus which is an obstacle that the dino is supposed to dodge by jumping.

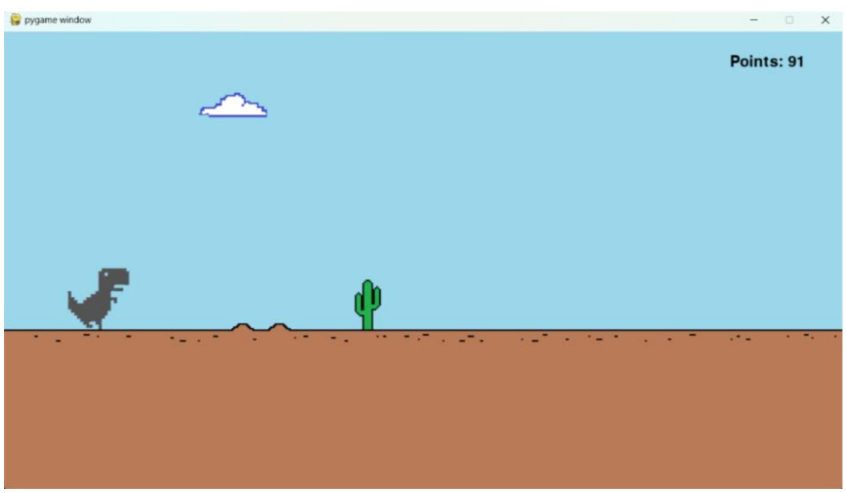

FIGURE 5. Screenshot of the Dinogame in pygame window

6. RESULT ANALYSIS

The model which was trained with Decision tree classifier has given a very good result on the test database. In the following classification report we can see that it achieved 96.09% accuracy with excellent precision, recall and f1-scores.

Accuracy of Decision Tree: 96.09375

	precision	recall	f1-score	support
0	0.96	0.96	0.96	221
1	1.00	0.96	0.98	219
2	0.92	0.96	0.94	200
accuracy			0.96	640
macro avg	0.96	0.96	0.96	640
weighted avg	0.96	0.96	0.96	640

FIGURE 5. Classification Report of Decision Tree

Another algorithm used was Random Forest classifier and this is outperformed Decision tree classifier and resulted in a whopping 99.21% accuracy with great precision, recall and f1-scores. We can easily say that model trained with Random Forest would be the best model to use for the classification of EEG emotion data.

Accuracy of Random Forest: 99.21875

	precision	recall	f1-score	support
0	0.99	0.99	0.99	221
1	1.00	1.00	1.00	211
2	0.99	0.99	0.99	208
accuracy			0.99	640
macro avg	0.99	0.99	0.99	640
weighted avg	0.99	0.99	0.99	640

FIGURE 6. Classification Report of Random Forest

7. CONCLUSION

The EEG-based emotion-aware Dinosaur game showcases innovative technology integration. The results demonstrate the potential of EEG-based emotion recognition in gaming applications. The current BCI game application is still a far cry from the sci-fi imaginations in various films and TV shows. The development of such applications is facing certain obvious problems including low transfer rates, high material costs, limited market investment, and a lack of BCI game-related content developers and art designers. This BCI approach enhances player engagement, immersion, and emotional investment in games, while also providing insights into the emotional responses of players. This innovative system contributes to the development of affective computing in gaming, demonstrating the vast potential for EEG-based emotion recognition to revolutionize the gaming industry. As a cutting-edge technology, BCI's development will have a non-negligible impact on the world. BCI technology in its infancy enjoys countless possibilities for future development.

REFERENCES

[1] Baraka Maiseli, Abdi T. Abdalla, Libe V. Massawe, "Brain-computer interface: trend,challenges and threats", Brain Informatics, (2023) 10:20, doi: 10.1186/s40708-023-00199-3

[2] [2] Samriya, J. K., Chakraborty, C., Sharma, A., Kumar, M., & Ramakuri, S. K. (2023). Adversarial ML-based secured cloud architecture for consumer Internet of Things of smart healthcare. IEEE Transactions on Consumer Electronics, 70(1), 2058-2065.

[3] [3] Manoranjan Dash et al.," Effective Automated Medical Image Segmentation Using Hybrid Computational Intelligence Technique", Blockchain and IoT Based Smart Healthcare Systems, Bentham Science Publishers, Pp. 174-182,2024

[4] [4] HaoYang Zhang, "Development of BCI Application in Gaming", International Journal of Research in Engineering and Science (IJRES), ISSN: 2320-9364, Volume 11 issue 3, March 2023, PP. 617-620

[5] [5] V. NavyaSree, Y. Surarchitha, A. M. Reddy, B. Devi Sree, A. Anuhya and H. Jabeen, "Predicting the Risk Factor of Kidney Disease using Meta Classifiers," 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Mysuru, India, 2022, pp. 1-6, doi: 10.1109/MysuruCon55714.2022.9972392.

[6] [6] Jordan J. Bird, Anikó Ekárt, Christopher D. Buckingham, Diego R. Faria, "Mental Emotional Sentiment Classification with an EEGbased Brain-Machine Interface", April 2019 The International Conference on Digital Image & Signal Processing (DISP'19), Oxford University, UK.

[7] [7] Ramakuri, S. K., Prasad, M., Sathiyanarayanan, M., Harika, K., Rohit, K., & Jaina, G. (2025). 6 Smart Paralysis. Smart Devices for Medical 4.0 Technologies, 112.

[8] [8] Pratibha R.Bhise, Sonali B.Kulkarni, Talal A. Aldhaheri, "Brain Computer Interface based EEG for Emotion Recognition System: A Systematic Review", Proceedings of the Second International Conference on Innovative Mechanisms for Industry Applications (ICIMIA 2020), IEEE Xplore Part Number: CFP20K58-ART; ISBN: 978-1-7281-4167-1, pp. 327-330

[9] [9] Manoranjan Dash et al.," Detection of Psychological Stability Status Using Machine Learning Algorithms", International Conference on Intelligent Systems and Machine Learning, Springer Nature Switzerland, Pp.44-51, 2022.

[10] [10] Georgios Prapas, Kosmas Glavas, Katerina D. Tzimourta, Alexandros T. Tzallas and Markos G. Tsipouras, "Mind the Move: Developing a Brain-Computer Interface Game with Left-Right Motor Imagery", MDPI Information Journal, Information 2023, 14, 354. https://doi.org/10.3390/info14070354

[11] [11] Manoranjan Dash, N.D. Londhe, S. Ghosh, et al., "Hybrid Seeker Optimization Algorithm-based Accurate Image Clustering for Automatic Psoriasis Lesion Detection", Artificial Intelligence for Healthcare (Taylor & Francis), 2022, ISBN: 9781003241409

[12] [12] Sebastian – Daniel Rosca1 and Monica Leba1, "Design of a Brain-Controlled Video Game based on a BCI System", MSE 2019, MATEC Web of Conferences 290, 010 (2019) https://doi.org/10.1051/matecconf /2019290010

[13] [13]Kumar, R.S., Nalamachu, A., Burhan, S.W., Reddy, V.S. (2024). A Considerative Analysis of the Current Classification and Application Trends of Brain–Computer Interface. In: Kumar Jain, P., Nath Singh, Y., Gollapalli, R.P., Singh, S.P. (eds) Advances in Signal Processing and Communication Engineering. ICASPACE 2023. Lecture Notes in Electrical Engineering, vol 1157. Springer, Singapore. https://doi.org/10.1007/978-981-97-0562-7_46.

[14] [14] Tommaso Colafiglio, Paolo Sorino, Angela Lombardi, Domenico Lofù and Tommaso Di Noia, "Predicting Human Emotions using EEG-based Brain computer Interface and Interpretable Machine Learning", CEUR-WS.org/Vol-3486/160.pdf

[15] [15] B. H. Rao et al., "MTESSERACT: An Application for Form Recognition in Courier Services," 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2022, pp. 848-853, doi: 10.1109/ICOSEC54921.2022.9952031.

[16] [16] Gary Garcia Molina, Tsvetomira Tsoneva, Anton Nijholt, "Emotional Brain-Computer Interfaces", International Journal of Autonomous and Adaptive Communications Systems, October 2009, DOI: 10.1109/ACII.2009.5349478

[17] [17] R. S. Kumar, K. K. Srinivas, A. Peddi and P. A. H. Vardhini, "Artificial Intelligence based Human Attention Detection through Brain Computer Interface for Health Care Monitoring," 2021 IEEE International Conference on Biomedical Engineering, Computer and Information Technology for Health (BECITHCON), Dhaka, Bangladesh, 2021, pp. 42-45, doi: 10.1109/BECITHCON54710.2021.9893646.

[18] [18] Aasim Raheel, Noshaba Liaqat, Mehr Dua, "A Neurocognitive Approach to Evaluate Mobile Game Player's Experience Using EEG", 2023 25th International Multitopic Conference (INMIC), DOI: 10.1109/INMIC60434.2023.10466105

[19] [19] S. K. Ramakuri, C. Chakraborty, S. Ghosh and B. Gupta, "Performance analysis of eye-state charecterization through single electrode EEG device for medical application," 2017 Global Wireless Summit (GWS), Cape Town, South Africa, 2017, pp. 1-6, doi:10.1109/GWS.2017.8300494.