

# GOVERNMENT COLLEGE OF ENGINEERING, SALEM-11 (An Autonomous Institution Affiliated to Anna University, Chennai)



# NeuroPlay: AI-Driven Brain Computer Interface for Seamless Mind Controlled Gaming Interaction and Real-Time Experience

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### PROJECT GUIDE

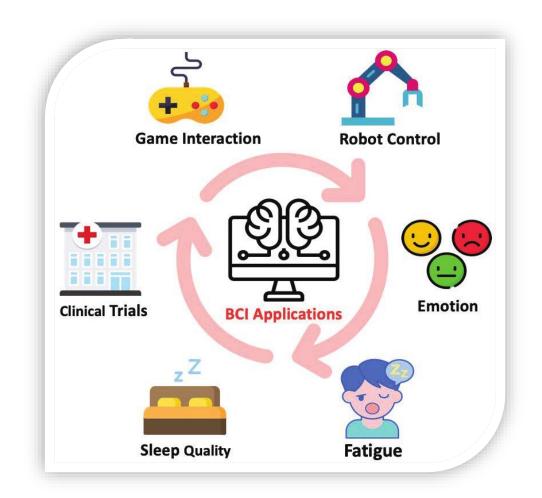
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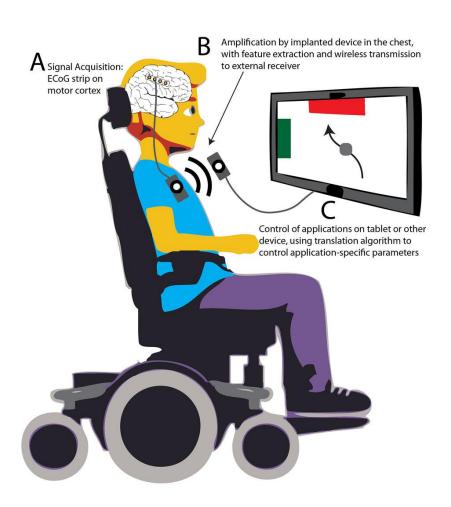
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### **OBJECTIVE**

- Develop an **AI-powered Brain-Computer Interface** system that enables **hands-free control** through **EEG signals**.
- Provide real-time, immersive experiences by interpreting brainwaves via AI-driven models.
- Enhance accessibility and interaction across various fields, enabling individuals with mobility impairments to engage through their thoughts.



### MOTIVATION OF THE PROJECT



The motivation behind our idea is that:

- Traditional method of interaction often rely on physical controllers, creating barriers for persons with disabilities.
- AI and BCI technology present a groundbreaking opportunity to create hands-free, intuitive interaction, particularly beneficial for those people with disability.
- So, This project is motivated by the desire to enhance accessibility and inclusion, enabling persons with disabilities to engage with technology and gaming through their thoughts.
- This project represents an innovative approach to **thought-driven interaction**, offering applications that can span beyond gaming, including healthcare, security, defense, communication and other domains.

### **INTRODUCTION**

- A Brain-Computer Interface (BCI) is a technology that enables direct communication between the brain and external devices by translating brain signals and activities into actionable commands that control external devices. BCIs are also known as brain-machine interfaces.
- AI models process and classify EEG data to recognize specific brain states (e.g., concentration, relaxation) and map them to actionable tasks (e.g., controlling a device or navigating a system).



# LITERATURE SURVEY

Year	Paper	Dataset	Methodology	Remarks
2022	Nieto,N., Peterson, V., Rufiner, H.L. et al. Thinking out loud, an open access EEG-based BCI dataset for Inner speech recognition.	EEG recordings during inner speech tasks, including pronounced speech, inner speech, and visualized conditions	Surface electroencephalography system	Limited sample size, focus solely on Spanish speakers, and potential confounds due to mixing imagined and actual speech.
2021	Aditya Srivastava, Sameer Ahmed Ansari, Prateek Mehta, "Think2Type: Thoughts to Text using EEG Waves",International Journal of Engineering Research & Technology	EEG motor movement/imagery database available on PhysioNet	FFT transformation, Ensemble Deep Learning model.	However, further validation and usability testing are necessary for real-world application

Year	Paper	Dataset	Methodology	Remarks
2021	VorontsovaD, Menshikov I, Zubov A, Orlov K, Lanikin A, et al. Silent EEG-SpeechRecognition Using Convolutional and Recurrent Neural Network with 85% Accuracy of 9 Words Classification. Sensors.	EEG recordings during inner speech tasks, including pronounced speech, inner speech, and visualized conditions.	Connectionist Temporal Classification (CTC) Automatic Speech Recognition (ASR) model	Themodel suffers from small vocabulary size, subject-dependency, and lack of comparison with other methods for EEG-based silent speech recognition.
2020	Ravi, Kamalakkannan & Rajkumar, R. & Raj, M.M. & Devi, S.S Imagined Speech Classification using EEG. Advances in Biomedical Science and Engineering.	EEG signals were recorded from 13 Volunteers average age of 21 years. The subjects were instructed to imagine English vowels 'a', 'e', 'i', 'o', and 'u' in response to visual stimuli.	Back Propagation Neural Network. Maximum classification accuracy of 44%, indicating room for improvement.	The study's exclusive focus on classifying English vowels may limit the generalizability of the findings to a broader range of speech sounds.

### PROPOSED SYSTEM

- An AI-powered Brain-Computer Interface (BCI) integrated platform that enables users to interact with digital experiences using their brain signals
- It provide face and voice-based recognition login system.
- This system aims to provide an **immersive**, **hands-free environment** where users can engage in
  - Gaming
  - Thought-to-Speech conversion
  - Emotion-based music
  - Virtual pets, Alerts & Insights .
- The system not only enhances entertainment but also helps in stress management, mental focus improvement, and physical fitness through brainwave-based feedback.



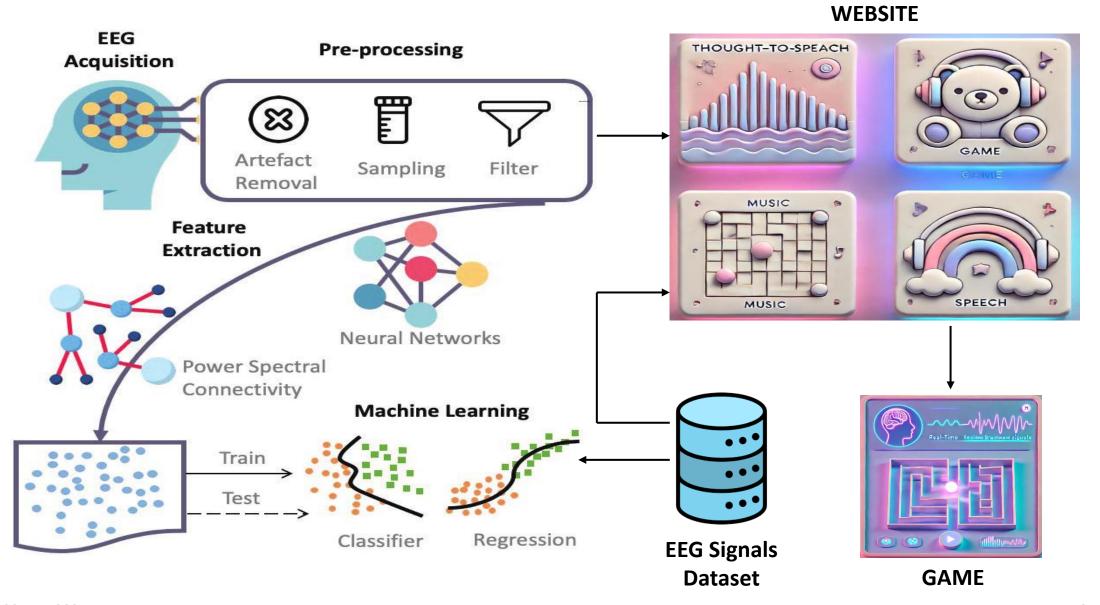








### **OVERALL ARCHITECTURE**



# **SOFTWARE REQUIREMENTS**

OPERATING SYSTEM

**OS**: Windows 11 Home

**OS Architecture**: 64 Bit

System Architecture: 64

• DEVELOPMENT TOOLS

**Visual Studio Code(Vs Code)** 

**Jupyter Notebook** 

CODE MAINTANENCE

Git and GitHub

• FRAMEWORK

Flask

- BRAIN COMPUTER INTERFACE
- DATABASE

**PostgreSQL** 











# HARDWARE REQUIREMENTS

PROCESSOR

**Brand**: AMD

Name: Ryzen 5 Hexa Core

Variant: 4500U

**Graphic Processor**: AMD Radeon Vega 8

**Number of Cores**: 6

• RAM

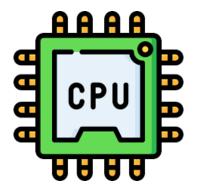
Capacity: 8 GB

Type: DDR4

Frequency: 2666 MHz

• STORAGE

Capacity: 256 GB







### LIST OF MODULES

1. REGISTER & LOGIN PAGE

- 3. BCI SIGNAL PROCESSING & AI MODEL TRAINING
- 4. GAME MODULE

2. HOME PAGE

- 5. THOUGHT-TO-SPEECH CONVERSION
- 6. ALERTS/INSIGHTS GENERATION













### **REGISTER & LOGIN PAGE**

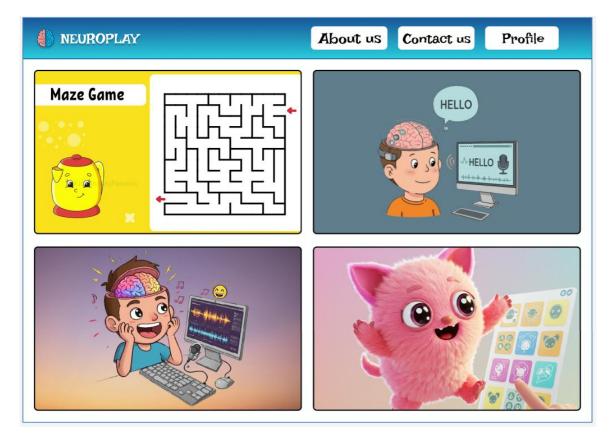
- This module provides an accessible authentication system using AI-powered face and voice recognition for users with disabilities.
- During registration, users provide personal details, upload face images or record voice samples for biometric authentication and while logging in allows users to use either traditional credentials (email/password) or biometric authentication, ensuring secure and easy access.





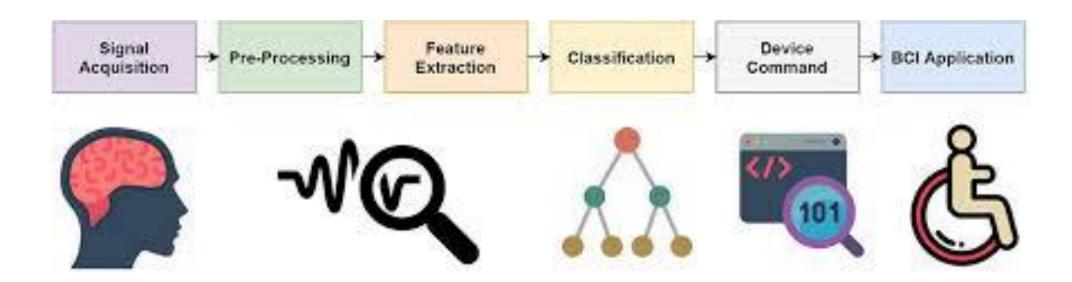
### **HOME PAGE**

- The home page acts as the **central dashboard**, displaying **user-specific data** and **interactive features**.
- Users can navigate to different functionalities, such as games, thought-to-speech, alerts/insights, emotion-based music and virtual pet assistance features which provides a better user experience.



### BCI SIGNAL PROCESSING & AI MODEL TRAINING

- This module processes brainwave signals (EEG-based datasets) to classify different mental states such as focus, relaxation, or intent.
- AI models are trained using machine learning techniques like CNNs or SVMs and that process those signals to map brain signals to corresponding user actions.
- Real-time processing ensures accurate and fast responses, enhancing the interactive experience.



### **GAME MODULE**

- A BCI-powered Maze game where users navigate a virtual maze using brain activity (simulated via EEG dataset-based AI model).
- The game **detects concentration** and **relaxation levels** to **control movement directions**, providing a **hands-free gaming experience**. It also shows **leaderboard** and **scores** of the users.
- Designed to improve cognitive abilities and focus while making the interaction engaging.



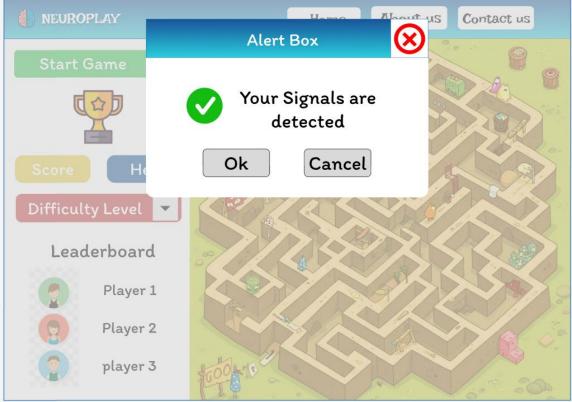
### THOUGHT-TO-SPEECH CONVERSION

- Enables users to **communicate** via **AI-driven text-to-speech technology**, especially **beneficial** for those with **speech impairments**.
- Brain signals (simulated through datasets) are interpreted into textual commands, which are then converted into speech.
- Helps in assistive communication, providing an inclusive solution for users with disabilities.



### **ALERTS/INSIGHTS GENERATION**

- Provides real-time alerts based on the user's cognitive state, stress levels, and engagement.
- AI-driven insights help users track their focus trends, cognitive improvements, and relaxation levels over time.
- Can be used in **sports**, **fitness**, and **daily activities** to **optimize mental well-being** and **performance**.



# ALGORITHM/TECHNIQUE USED

### 1. Frontend (User Interface)

HTML, CSS, JavaScript – For basic website structure and styling with interactive UI



Python (Flask) – For handling requests and AI model and for

communication between front and back end

### 3. Database (Data Storage)

PostgreSQL – For storing user details, voice and user images

### 4. AI & Machine Learning Models

SVM – For training AI models

DeepFace – For face recognition

Resemblyzer – For voice recognition

### 5. Brain-Computer Interface (BCI) Integration

OpenBCI / Neurosky MindWave – EEG signal collection processing



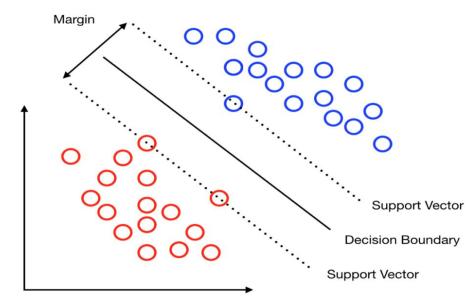






### **SUPPORT VECTOR MACHINE**

- Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks.
- It is particularly effective in **high-dimensional spaces** and **works well** when there is a **clear** margin between different classes.
- It finds the **best possible hyperplane** (**decision boundary**) that **separates different classes** in the **feature space**.
- BCI signal classification to recognize different mental states based on brainwave data.



### STEPS IN PROCESSING BCI DATA USING SVM

### **Step 1: Data Collection (EEG Signals Acquisition)**

- ✓ Brainwave signals are collected using an EEG Dataset or BCI sensor.
- ✓ These signals represent different brain activities (e.g., concentration, relaxation, movement intention).

### **Step 2: Preprocessing (Noise Removal & Normalization)**

- ✓ EEG signals often contain noise from muscle movements, blinks, and environmental interference.
- ✓ Techniques like Bandpass Filtering, Fast Fourier Transform (FFT), and Wavelet Transform are used to clean the data.
- ✓ Normalization is applied to scale data between 0 and 1 for better performance.

### **Step 3: Feature Extraction (Selecting Key Signal Features)**

- ✓ The EEG signals are transformed into meaningful features.
- **✓** Common Features Extracted:

Power Spectral Density (PSD) – Measures signal power in different frequency bands.

Wavelet Coefficients – Captures time-frequency information.

Statistical Features – Mean, variance, and entropy of signals.





### **Step 4: Training the SVM Model**

✓ The extracted features are used to train an SVM classifier. The model learns to distinguish between different mental states or user intentions.

### **✓** Kernel Selection:

Linear Kernel – Used when the data is linearly separable.

RBF (Radial Basis Function) Kernel – Used for non-linear classification.

### **Step 5: Model Evaluation & Testing**

- ✓ The trained model is tested using real-time EEG signals.
- ✓ Accuracy, precision, recall, and F1-score are used to evaluate the model's performance.

### **Step 6: Real-Time Prediction & Integration**

✓ When the user interacts, the trained SVM model classifies their brainwave signals and based on the predicted mental state,

### ✓ Action is triggered:

Game Control – Moving objects based on concentration levels.

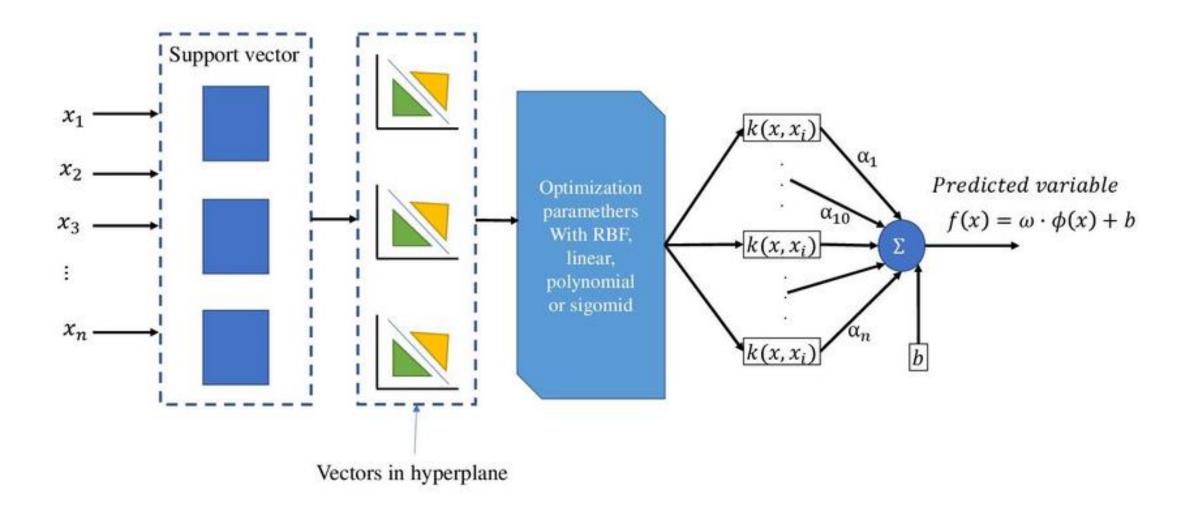
Thought-to-Speech – Generating speech from classified thoughts.

Alert System – Sending alerts based on stress detection.





### SUPPORT VECTOR MACHINE ARCHITECTURE



### **RESULT & DISCUSSION**

• The **Support Vector Machine** (SVM) model achieved an **accuracy** of **94.96**% in classifying mental states into **Relaxed**, **Stressed**, and **Concentrated** based on EEG signal data.



Label	Precision	Recall	F1-Score	Support
Relaxed / Idle (0.0)	0.97	0.94	0.95	167
Stressed (1.0)	0.94	0.91	0.93	167
Concentrated	0.94	1.00	0.97	162
Accuracy			0.95	496
Macro Avg	0.95	0.95	0.95	496
Weighted Avg	0.95	0.95	0.95	496

### **CONCLUSION**



- The proposed BCI system successfully classifies EEG signals into mental states such as Relaxed, Stressed, and Concentrated using a Support Vector Machine (SVM) model.
- The system achieved a **high accuracy** of **94.96%**, proving its **effectiveness in recognizing brain activity patterns.**
- This project demonstrates the potential of integrating AI and BCI for real-time, hands-free interaction and mental state monitoring.
- Results confirm the **system's potential** in **assistive technology, neurofeedback**, and **hands-free interaction**.

### **FUTURE WORK**



- Deploy the system in real-time with wearable EEG headsets for continuous feedback.
- Enhance the system by integrating deep learning models (e.g., CNNs, LSTMs) for improved performance.
- Expand classification to include more mental states such as fatigue, confusion, or drowsiness.
- Improve accessibility by integrating with virtual assistants or IoT-based applications.
- Explore **multi-modal authentication** (combining BCI, face, and voice recognition) for **higher security**.

### REFERENCES



- 1. N. Kobayashi, T. Nemoto and T. Morooka, "High Accuracy Silent Speech BCI Using Compact Deep Learning Model for Edge Computing," 2023 11th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea, Republic of, 2023, pp. 1-6, doi: 10.1109/BCI57258.2023.10078589.
- 2. Nieto, N., Peterson, V., Rufiner, H.L. et al. Thinking out loud, an open-access EEG-based BCI dataset for inner speech recognition. Sci Data 9, 52 (2022). https://doi.org/10.1038/s41597-022-011472
- 3. Shah U, Alzubaidi M, Mohsen F, Abd-Alrazaq A, Alam T, Househ M. The Role of Artificial Intelligence in Decoding Speech from EEG Signals: A Scoping Review. Sensors (Basel). 2022 Sep 15;22(18):6975. doi: 10.3390/s22186975. PMID: 36146323; PMCID: PMC9505262.
- 4. C. Cooney, R. Folli and D. Coyle, "A Bimodal Deep Learning Architecture for EEG-fNIRS Decoding of Overt and Imagined Speech," in IEEE Transactions on Biomedical Engineering, vol. 69, no. 6, pp. 1983-1994, June 2022, doi: 10.1109/TBME.2021.3132861.

