NEUROPLAY: UNLOCKING THE POWER OF AI-DRIVEN BRAIN-COMPUTER INTERFACE FOR SEAMLESS MIND-CONTROLLED GAMING INTERACTION AND IMMERSIVE REAL-TIME EXPERIENCE

Abstract

Over the past decade, we are limited to wired controllers for interaction with computers; today, we have wireless controllers have become the normal. Looking ahead, within the next few decades promise a future where no physical controllers are needed at all – systems will respond directly to our intentions and thoughts. This project takes a pioneering step toward that future by creating an accessible system that integrates artificial intelligence (AI) and brain-computer interface (BCI) with face and voice recognition, enabling hands-free, intelligent interaction, especially for users with physical disabilities. Traditional login methods often exclude individuals with physical challenges. Our system enables face and voice-based registration and login, while brain signals (EEG) are processed using bandpass filtering, FFT, and wavelet transforms to extract features. These features are classified using Support Vector Machine (SVM) to detect mental states like focus or relaxation. The system also includes modules like a maze game, thought-to-speech output, and real-time alerts, promoting inclusive, intelligent interaction — a move toward controller-free computing.

Keywords: AI; BCI; Face Recognition; Voice Recognition; EEG; SVM; Accessibility; Mental State Detection

1.INTRODUCTION

In recent years, the evolution of human-computer interaction (HCI) has taken a remarkable leap forward with the emergence of Brain-Computer Interfaces (BCIs). Traditional methods such as keyboard, mouse, and touchscreen have served as primary means for humans to interact with digital systems. However, they demand motor ability, coordination, and physical access, which may not be feasible for everyone, especially individuals with physical disabilities. As a result, a need for a more intuitive, direct, and inclusive form of interaction has arisen — one that bridges the gap between the human mind and machines. The Brain-Computer Interface stands as a pioneering technology in this domain, allowing users to control systems or **communicate without the need for any physical movement**.

A **Brain-Computer Interface (BCI)** is a communication system that enables users to send commands directly from their brain to an external device. This is achieved by capturing the brain's electrical activity, typically through non-invasive methods like Electroencephalography (EEG), and translating those signals into machine-interpretable instructions using signal processing and machine learning algorithms. BCIs have shown potential in various applications such as assistive communication devices, neurogaming, smart environments, rehabilitation, and more recently, secure authentication and accessibility systems.

At the heart of modern BCI systems lies **Artificial Intelligence (AI)**, which plays a critical role in signal interpretation, feature extraction, and classification. Brain signals are naturally noisy, non-linear, and vary greatly across individuals and sessions. AI-based models, particularly machine learning algorithms like Support Vector Machines (SVM), Neural Networks, and Deep Learning, are essential to learn patterns from brain activity and predict mental states such as **attention, relaxation, cognitive load, or motor intent**. The integration of AI enhances the accuracy, robustness, and adaptability of BCI systems.

In this project, we present an AI-powered BCI-based system that enables a user to **register, log in, and interact with a web platform** using only their face, voice, and brain signals. The system is designed with a special focus on **accessibility for people with disabilities**, aiming to minimize or eliminate the need for physical interfaces. The motivation behind this project stems from the desire to create inclusive and future-ready systems. While biometric authentication (face and voice) has become increasingly common in smartphones and secure systems, this creates barriers for users with limited mobility. By combining AI-driven BCI with biometric methods, this project introduces a hands-free solution that is not only secure but also highly accessible. It allows users to both authenticate and operate systems using only their natural biometric and cognitive signals, with no need for keyboards, touch, or voice commands post-login. Fig.1. shows the Process flow of brain computer interface system

Ultimately, this project envisions a future where **human thought becomes the primary mode of interaction with digital systems**. It serves as a demonstration of the potential synergy between BCI, AI, and biometric technologies, offering a glimpse into the next generation of intelligent human-computer interaction. Whether for users with special needs, gamers seeking immersive control, or researchers exploring cognitive states, this system paves the way for a new paradigm of mind-controlled digital experiences. Furthermore, our work not only provides a practical application but also demonstrates the potential of merging AI, BCI, and biometric recognition to create futuristic, accessible technology.

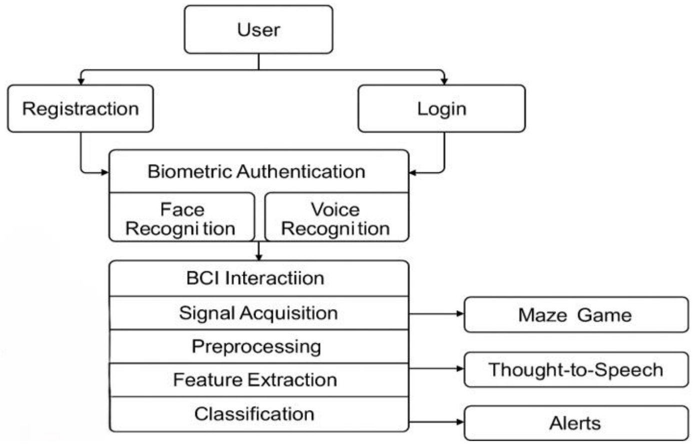

Fig.1. Process flow of brain computer interface system

The main goal of this work is outlined below:

- Develop an AI-powered Brain-Computer Interface system that enable hands-free authentication using face and voice recognition.
- Integrate machine learning models for accurately classify mental states using EEG signal processing.
- Provide a secure and contactless user interaction experience and assist physically disabled users through thought-based control.
- Build real-time applications like maze game and thought-to-speech.
- Demonstrate the fusion of BCI, AI, and biometric technologies.

2. RELATED WORK

The advancement of Brain-Computer Interface (BCI) technology has opened new frontiers in enabling direct communication between the human brain and external systems, with particular attention to decoding inner or silent speech through EEG signals. Recent studies have shown increasing interest in leveraging deep learning models for silent speech recognition, especially due to their effectiveness in extracting spatiotemporal features from EEG data. Kobayashi et al. (2023) proposed a compact deep learning model suitable for edge computing environments, achieving high accuracy in silent speech decoding, and highlighting the practicality of real-time BCI systems on resource-constrained devices [1]. Similarly, the availability of open-access datasets, such as the one presented by Nieto et al. (2022), facilitates research in inner speech decoding by providing a rich source of labelled EEG signals associated with imagined or silent speech tasks [2].

A number of studies have conducted comprehensive reviews to assess the role of artificial intelligence in decoding speech from EEG signals. Shah et al. (2022) presented a scoping review that underscores the efficacy of AI-based approaches, particularly deep learning models, in extracting meaningful patterns from brain signals and decoding speech components with notable accuracy [3]. Furthermore, Cooney et al. (2022) introduced a bimodal deep learning framework that combines EEG and fNIRS modalities to decode both overt and imagined speech, offering enhanced performance through multimodal signal integration [4]. While most works focus on classification accuracy, emotion recognition has also been explored as an auxiliary task to improve decoding precision. Houssein et al. (2022) provided an in-depth analysis of human emotion recognition using machine learning on EEG data, which could be integrated into silent speech systems for sentiment-aware communication [5].

Several researchers have emphasized the importance of context-based training and transfer learning to improve silent speech recognition. Rekrut et al. (2022) proposed a transfer-based approach that classifies words in natural reading tasks, aiming to bridge the gap between training and real-world application [6]. Vorontsova et al. (2021) achieved a remarkable 85% accuracy in recognizing nine different silent speech words using a hybrid model that integrates convolutional and recurrent neural networks, highlighting the potential of such architectures for sequential data processing [7]. The same authors further validated their model in clinical and cognitive neuroscience contexts, suggesting possible applications in assistive communication for people with speech impairments [10].

Additional research has focused on decoding semantic categories rather than exact words. Rekrut et al. (2021) examined EEG data collected during silent speech imagination tasks and demonstrated that deep learning models could effectively differentiate between semantic categories of imagined words [8]. Another innovative concept is explored by Shahid et al. (2021), who developed "EmoWrite", a sentiment-aware BCI system that performs thought-to-text conversion based on the emotional tone detected in EEG signals [9]. This integration of affective computing within BCIs is particularly relevant for enhancing human-computer interaction in emotionally charged communication scenarios.

Apart from traditional EEG recordings, invasive techniques like stereotactic electroencephalography (sEEG) have also been employed to identify discriminative features for overt and imagined speech, as shown by Meng et al. (2021) [12]. This work reveals deeper neural representations of speech, though it comes with increased ethical and procedural constraints. In contrast, non-invasive methods remain the preferred choice for scalable applications. For instance, Lee et al. (2021) adopted a deep metric learning strategy for decoding imagined speech, which allowed for more intuitive BCI communication by clustering similar speech patterns in latent space [13]. Similarly, Hamedi et al. (2020) developed a system that won the 3rd Iranian BCI Competition, demonstrating the competitive performance of optimized machine learning models in imagined speech decoding [14].

The use of EEG for silent speech recognition is not limited to word-level decoding but extends to syllable-level and character-level tasks. Srivastava et al. (2020) introduced the "Think2Type" system, which translates EEG signals into text by recognizing individual characters and assembling them into meaningful sentences, presenting an innovative solution for communication aids [15]. Arteiro et al. (2020) also explored silent speech recognition in decentralized messaging applications, emphasizing the potential for secure and privacy-preserving communication using BCIs [16]. Moreover, Lee et al. (2020) investigated spatial and temporal patterns in EEG during imagined and overt speech, concluding that unique representations exist for different types of speech that could be leveraged by neural networks for improved decoding [17].

Finally, Sarmiento et al. (2019) demonstrated the feasibility of recognizing silent speech syllables through EEG analysis in natural language settings. Their approach contributes to a better understanding of how different linguistic units are processed in the brain during silent articulation, which is crucial for developing linguistically informed BCI systems [18]. Overall, these contributions collectively signify a shift towards more intelligent, adaptive, and user-centric brain-computer interfaces for silent speech recognition.

3. MATERIALS AND PROPOSED METHOD

The Brain-Computer Interfaces (BCIs) represent a revolutionary field in human-computer interaction, allowing direct communication between the brain and external systems without muscular movement. The proposed system includes a comprehensive pipeline for developing an AI-driven Brain-Computer Interface (BCI) application that can interpret and classify human cognitive states using Electroencephalography (EEG) signals. It integrates signal acquisition, preprocessing, feature engineering, classification using machine learning algorithms, and real-time inference. The architecture ensures that brainwave data is systematically processed and analyzed to perform accurate mental state recognition and application-specific control. The architecture of the proposed method is shown in Fig.2.

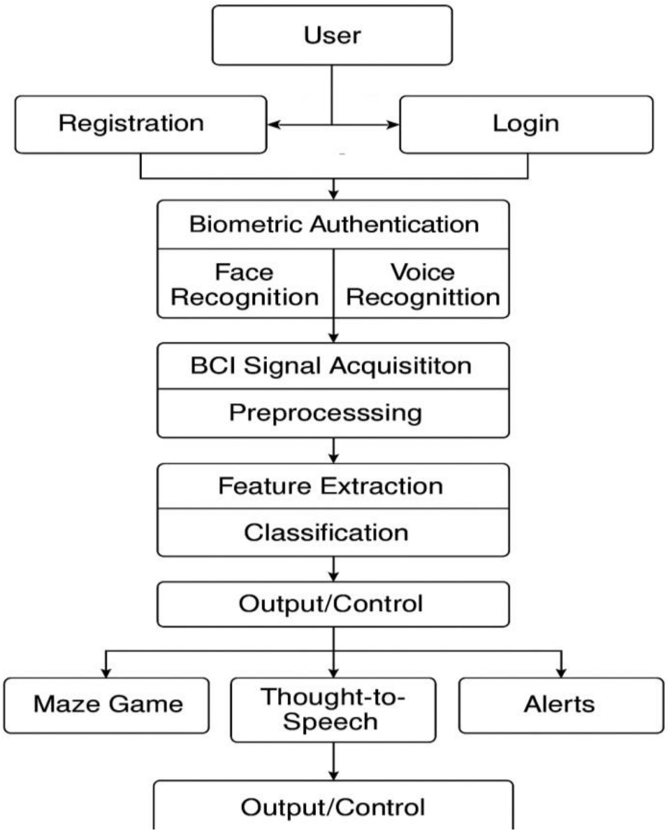

Fig.2. Architecture of the proposed method

3.1 Authentication (Face & Voice based Recognition)

In the proposed AI-based Brain-Computer Interface (BCI) system, authentication plays a vital role in ensuring that only authorized individuals gain access to the BCI-controlled environment. Unlike conventional password-based systems, this project adopts a **unified biometric authentication approach** that combines **facial recognition** and **voice recognition** for user registration and login. This enhances the system's usability, security, and user experience, especially in contexts where users may have physical impairments.

3.1.1 Overview of Biometric Authentication

Biometric authentication utilizes unique physiological or behavioural characteristics for identity verification. In this system, two distinct biometric traits are used:

- **Facial Recognition**: Verifies identity based on the geometric features of a user's face.
- **Voice Recognition**: Confirms identity by analysing the user's vocal characteristics, including pitch, tone, and speech patterns.

The combination of both modalities ensures **multimodal authentication**, significantly reducing the risk of spoofing or unauthorized access.

3.1.2 Registration Process

During user registration, the following steps occur:

- The system prompts the user to **look into the webcam** to capture multiple facial images under varying angles and lighting conditions.
- Simultaneously, the user is asked to **speak a predefined passphrase**, which is recorded using the system microphone.
- Facial embeddings are generated using pre-trained deep learning models (e.g., FaceNet, OpenCV with Haar Cascades or Dlib).
- Voiceprint features are extracted using techniques like **MFCC (Mel-Frequency Cepstral Coefficients)** and stored securely.
- Both sets of biometric data are linked and stored in an encrypted format within the user profile in the database.

3.1.3 Login Process

To log in, the user must perform the following:

- **Face Verification**: The webcam captures a live image of the user's face, which is compared with the stored embeddings using a similarity threshold.
- **Voice Verification**: The user is asked to repeat the passphrase. The system extracts voice features and compares them with the registered voiceprint.
- Only if **either facial or voice matches** exceed the defined confidence threshold, the user is successfully authenticated and granted access to the system dashboard.

3.1.4 Security, Privacy Considerations and benefits

- **Encryption**: All biometric data is stored in an encrypted format to prevent misuse.
- **Liveness Detection**: Optional liveness checks can be integrated to avoid spoofing through photos or recorded voices.
- **Data Retention Policy**: User biometric data is retained only as long as necessary and is deleted upon user request or account removal.
- **Touchless Access**: Beneficial for users with limited mobility.

- **Improved Security**: Dual authentication using face and voice reduces vulnerability to attacks.
- **User-Friendly**: No need to remember or enter passwords manually.

By incorporating face and voice-based biometric authentication, the proposed system aligns with modern, secure access standards while offering a seamless and inclusive experience for users of the AI-based BCI platform

3.2. Data Collection (EEG Signals Acquisition)

The initial phase of the proposed system involves collecting neural signals, particularly **Electroencephalography (EEG)** data, which captures the brain's electrical activity through non-invasive electrodes placed on the scalp. EEG data reflects cognitive states such as attention, relaxation, motor intention, and emotional responses, making it highly suitable for BCI applications.

Data acquisition can be done in two primary ways:

3.2.1. Using Public Datasets:

- Datasets such as the **DEAP (Dataset for Emotion Analysis using Physiological signals)**, **BCI Competition IV**, and **EEG Eye State dataset** contain labelled EEG recordings gathered from multiple subjects performing various tasks like motor imagery, affective responses, or mental arithmetic.

3.2.2. Using EEG Devices:

- Consumer-grade and research-grade devices such as **Emotiv EPOC+, NeuroSky MindWave, OpenBCI**, or **Muse** can be used to gather real-time EEG data. These devices typically offer 1–16 channels with sampling rates from 128 Hz to 512 Hz, sufficient for low-latency BCI applications.

Each EEG recording consists of voltage fluctuations in different frequency bands—delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–100 Hz)—that carry specific cognitive information.

3.3. Preprocessing (Noise Removal & Normalization)

EEG signals are inherently noisy due to artifacts generated by muscle movements (Electromyogram), eye blinks (Electrooculogram), and environmental disturbances. To ensure clean and analysable data, several preprocessing techniques are applied:

3.3.1. Filtering

- **Bandpass Filters** (commonly 0.5–50 Hz) are applied to retain only the frequency range where meaningful brain signals exist.
- **Notch Filtering** (e.g., at 50 or 60 Hz) is used to eliminate power line interference.

3.3.2. Artifact Removal

- **Independent Component Analysis (ICA)** can separate EEG signals from unwanted components like eye movement and muscle artifacts.
- **Wavelet Denoising** decomposes the EEG signal into different scales and suppresses noise in each frequency band.

3.3.3. Signal Transformation

- **Fast Fourier Transform (FFT)** converts time-domain signals into frequency-domain for spectral analysis.
- **Wavelet Transform (WT)** offers time-frequency localization, capturing transient features effectively.

3.3.4. Normalization

Post-processing, the signals are scaled using techniques such as **Min-Max Normalization** or **Z-score normalization**, ensuring all features are on a common scale. This improves the training efficiency and convergence rate of machine learning algorithms.

3.4. Feature Selection (Selecting Key Signal Features)

Once the signals are cleaned, the next phase is feature extraction, where **meaningful data representations** are generated from raw EEG signals. The goal is to reduce dimensionality while preserving relevant information for classification.

Key features used in the proposed system include:

3.4.1. Spectral Features

- **Power Spectral Density (PSD)**: Indicates the power distribution across different frequency bands. It's computed using Welch’s method or FFT and is critical for identifying cognitive states.

3.4.2. Time-Frequency Features

- **Wavelet Coefficients**: Extracted via Discrete Wavelet Transform (DWT), these coefficients provide high-resolution signal information across multiple scales.

3.4.3. Statistical Features

- **Mean**, **Standard Deviation**, **Variance**, **Skewness**, **Kurtosis**, and **Entropy** are computed from EEG signal segments to capture their distribution, symmetry, and randomness.

3.4.4. Nonlinear Features

- **Hjorth Parameters**, **Fractal Dimension**, and **Approximate Entropy** are often employed to capture the complex nonlinear dynamics of brain signals.

These features are organized into a feature vector, typically of fixed size, that represents the neural state for each time window (e.g., every 2 seconds).

3.5 Model Training (Using SVM Classifier)

The extracted feature vectors are used to train a machine learning model capable of classifying mental states. The **Support Vector Machine (SVM)** classifier is selected due to its:

- Effective to high-dimensional spaces.
- Good generalization even with small datasets.
- Robust to noisy data.
- Ability to work well with both linear and non-linear data.
- Binary and multi-class classification.

3.5.1. Kernel Selection

- **Linear Kernel**: Applied when data is linearly separable.
- **Radial Basis Function (RBF) Kernel**: Used for non-linearly separable data. It maps data to higher dimensions to find a hyperplane that best separates classes.

3.5.2. Hyperparameter Tuning

- Parameters like the **penalty term (C)** and **kernel coefficient (γ)** are optimized using grid search or random search methods combined with **K-fold cross-validation** (typically K=5 or 10) to avoid overfitting.

3.5.3. Model Training Procedure

- Data is split into **training sets (**70-80% of the original data) **and validation sets** (30-20% of the original data).
- Features are input into the SVM to build a model that learns decision boundaries.
- The model stores support vectors and decision hyperplanes for later classification.

3.6 Model Evaluation and Testing

After training, the model is tested using a separate **test set** (e.g., 20–30% of the original data) to evaluate its performance. The following metrics are computed:

- **Accuracy**: Overall percentage of correctly classified samples.
- **Precision**: Correctly predicted positive observations divided by total predicted positives.
- **Recall (Sensitivity)**: Correctly predicted positives divided by total actual positives.
- **F1-Score**: Harmonic mean of precision and recall.
- **Confusion Matrix**: Summarizes the number of true positives, false positives, true negatives, and false negatives.

These metrics help determine whether the system is suitable for deployment. **Receiver Operating Characteristic (ROC)** curves and **Area Under Curve (AUC)** scores are also plotted to analyse the model's ability to distinguish between classes.

3.7 Real-Time Prediction and System

In the final phase, the trained model is integrated into a real-time prediction system. The EEG device continues to collect data, and the following steps are executed on-the-fly:

3.7.1. Live Signal Acquisition

- EEG signals are captured continuously and split into fixed-length time windows (e.g., 2s, 5s).

3.7.2. Live Preprocessing

- Each signal segment undergoes real-time denoising and normalization.

3.7.3. Live Feature Extraction

- Feature vectors are extracted in real-time using the same methods as in the training phase.

3.7.4. Prediction

- The pre-trained SVM model classifies the incoming feature vector into a specific mental state (e.g., attention, relaxation, intention to move).

3.7.5. Action Execution

Based on the predicted state, the system triggers an appropriate response:

- **Gaming**: User controls virtual objects using concentration.
- **Healthcare**: Stress detection alerts for neurofeedback or therapeutic intervention.
- **Thought-to-Speech**: Silent communication via EEG-triggered speech synthesis for patients with paralysis.

The system ensures **low latency**, **high throughput**, and **user-specific adaptability**, making it suitable for applications in assistive technology, neuro-gaming, and mental health monitoring.

4. ALOGORITHM AND WORKING PROCESS

SUPPORT VECTOR MACHINE (SVM)

4.1 Introduction

Support Vector Machine (SVM) is a **supervised machine learning algorithm** primarily used for **classification** tasks, and in some cases, regression problems. SVM has gained popularity due to its **high accuracy**, ability to handle **high-dimensional data**, and robustness in finding **optimal hyperplanes** to separate data classes. In the context of a Brain-Computer Interface (BCI) system, SVM is employed to classify EEG signal patterns that represent various cognitive states such as attention, relaxation, or motor imagery. Its ability to efficiently **handle non-linear separability and high-dimensional feature vectors** makes it a fitting choice for EEG signal classification.

4.2 Basic Concepts and Terminologies

4.2.1. Goal of SVM

To find the **optimal hyperplane** that separates the data points of different classes with the **maximum margin**.

4.2.2. Key Concepts

- **Hyperplane**: A decision boundary that separates different classes. In 2D, it's a line; in 3D, it's a plane; in higher dimensions, it's a hyperplane.
- **Support Vectors**: Data points that are closest to the hyperplane and directly influence its position. They are critical elements of the training set.
- **Margin**: The distance between the hyperplane and the nearest support vectors. SVM tries to **maximize this margin**.

4.2.3. Types of SVM

- **Linear SVM**: Used when data is linearly separable.
- **Non-Linear SVM**: Uses **kernel functions** to project data into higher dimensions where it becomes linearly separable.

4.2.4. Common Kernel Functions

1. **Linear Kernel**: Suitable for linearly separable data.
2. **Polynomial Kernel**: Maps input features into a polynomial space.
3. **Radial Basis Function (RBF) Kernel**: Also called the Gaussian kernel, used for non-linear separation.
4. **Sigmoid Kernel**: Functions like a neural network activation function.

4.3 Working

SVM finds the optimal hyperplane that distinctly classifies the data points into different categories by maximizing the margin between the classes. It uses support vectors to define this boundary and can utilize kernel functions to perform non-linear classification. For example, in our BCI project, EEG features are fed into the SVM which then learns to classify them into cognitive states based on their extracted patterns.

4.3.1. Data Representation

Assume we have a dataset of EEG features:

$$\{(x^1, y^1), (x^2, y^2), \dots, (x_n, y_n)\}$$

Where:

- $x_i \in \mathbb{R}^n$ is the feature vector extracted from EEG signals
- $y_i \in \{-1, +1\}$ represents the class labels (e.g., attention = +1, relaxation = −1)

4.3.2. Finding the Optimal Hyperplane

A hyperplane in n-dimensional space can be represented as:

$$w \cdot x + b = 0$$

Where:

- w is the weight vector
- b is the bias

The decision function is:

$$f(x) = sign(w \cdot x + b)$$

The objective is to **maximize the margin**:

$$Margin = 2 / ||w||$$

Hence, the optimization problem becomes:

$$Minimize\ (1/2) * ||w||^2$$

Subject to the constraint:

$$y_i (w \cdot x_i + b) \geq 1\ for\ all\ i$$

4.3.3. Handling Non-Linearly Separable Data

To handle non-linear cases, we introduce **slack variables** ξ_i and a **penalty parameter** C:

$$Minimize\ (1/2) * ||w||^2 + C * \sum_i \xi_i$$

Subject to:

$$y_i (w \cdot x_i + b) \geq 1 - \xi_i, \qquad \xi_i \geq 0$$

4.3.4. Kernel Trick

To transform non-linearly separable data into a higher-dimensional space:

$$K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$$

Common kernels:

- **Linear**: $K(x, y) = x \cdot y$
- **Polynomial**: $K(x, y) = (x \cdot y + c)$^d
- **RBF**: $K(x, y) = \exp(-\gamma \|x - y\|^2)$

In our BCI system, the **RBF kernel** is ideal for EEG classification due to its ability to model complex, non-linear brainwave patterns.

4.3.5. Prediction

For a new EEG feature vector x, the prediction is given by:

$$f(x) = sign(\sum_i \alpha_i\, y_i\, K(x_i, x) + b)$$

Where α_i are the **Lagrange multipliers** obtained during training.

4.4 Architecture

Fig.3. shows the Architecture of support vector machine.

4.4.1. Input Layer: EEG Feature Vectors

- **Input**: A set of feature vectors derived from raw EEG signals.
- Each EEG signal is preprocessed and transformed into a **feature vector** $x_i \in \mathbb{R}^n$.
- These features may include:
  - Band power (alpha, beta, theta waves)
  - Hjorth parameters
  - Entropy measures
  - Time-domain statistics
- Each vector x_i is associated with a label $y_i \in \{+1, -1\}$:
  - +1 might represent **focused/attentive** state
  - −1 might represent **relaxed/drowsy** state

4.4.2. Hyperplane Construction: Core of the SVM

- SVM aims to construct a **hyperplane** that best separates the two classes in the feature space.
- The hyperplane is represented as:

  $$w \cdot x + b = 0$$

  Where:

  w = weight vector (determines orientation of hyperplane)

  b = bias term (offsets the hyperplane)

- The goal is to find the **optimal hyperplane** with the **maximum margin**, i.e., the largest distance between the hyperplane and the nearest data points of each class.

4.4.3. Support Vectors: Boundary Points

- **Support Vectors** are the data points that lie closest to the hyperplane and are critical in defining the decision boundary.
- These vectors satisfy the condition:

$$y_i (w \cdot x_i + b) = 1$$

Only the support vectors influence the position and orientation of the hyperplane; other data points are irrelevant in the final model.

4.4.4. Margin Maximization

- The distance (margin) between the hyperplane and the support vectors is:

$$\text{Margin} = 2 / ||w||$$

- The optimization problem becomes:

$$\text{Minimize } (1/2) * ||w||^2$$
$$\text{Subject to: } y_i (w \cdot x_i + b) \geq 1$$

- This ensures a large margin and avoids overfitting.

4.4.5. Handling Non-linear Data: Soft Margin & Slack Variables

- Real-world EEG data is often **noisy** and **non-linearly separable**.
- Introduce **slack variables $\xi_i \geq 0$** to allow some misclassifications:

$$y_i (w \cdot x_i + b) \geq 1 - \xi_i$$

- The modified optimization becomes:

$$\text{Minimize } (1/2) * ||w||^2 + C \sum \xi_i$$

Where:

C is a penalty parameter that controls trade-off between **margin size** and **classification error**.

4.4.6. Kernel Trick: Mapping to Higher Dimensions

- When data is **not linearly separable**, SVM uses **kernel functions** to implicitly project data into a higher-dimensional space:

$$K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$$

Common kernel functions:

- **Linear Kernel**: $K(x, y) = x \cdot y$
- **Polynomial Kernel**: $K(x, y) = (x \cdot y + c)^d$
- **RBF (Gaussian) Kernel**: $K(x, y) = \exp(-\gamma ||x - y||^2)$

In EEG classification, the **RBF kernel** is widely used because it can model complex, non-linear patterns in brainwave data.

4.4.7. Prediction Layer: Decision Function

- For a new input EEG feature vector x, the predicted class label is computed as:

$$f(x) = \text{sign}\left(\sum_i \alpha_i y_i K(x_i, x) + b \right)$$

Where:

α_i are the **Lagrange multipliers** determined during training.

$K(x_i, x)$ is the kernel function between support vector x_i and input x.

- The output is:

+1 → Attention

−1 → Relaxation

0 → Stressed

4.4.8. Training Phase

- During training, SVM:
  - Identifies support vectors
  - Computes Lagrange multipliers α_i
  - Determines optimal w and b
- These parameters are saved for use during prediction.

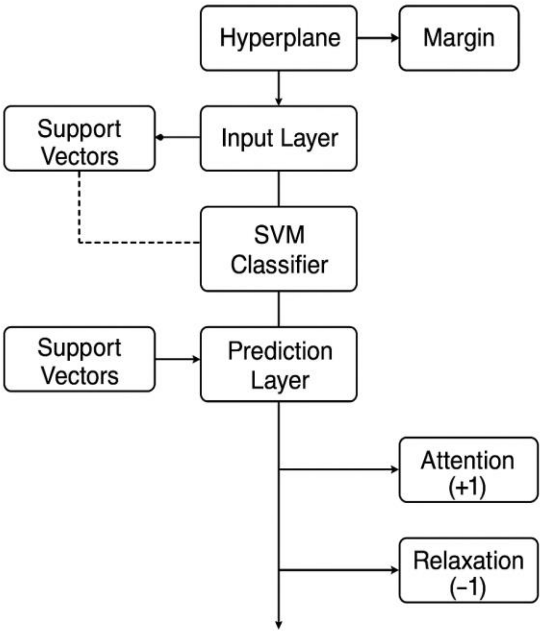

Fig.3. Architecture of support vector machine

4.5 Advantages

- Works well with **high-dimensional data**
- Robust against **noise and overfitting**
- Kernel trick allows **flexibility in decision boundaries**
- Efficient for **small-to-medium EEG datasets**

5. RESULT

In this project, a Support Vector Machine (SVM) classifier was trained to categorize EEG signals into three cognitive states: relaxed or idle (label 0), stressed (label 1), and concentrated (label 2). The dataset included a balanced distribution of mental states with 819 instances of relaxed, and 830 each for stressed and concentrated.

The model was evaluated using a testing dataset of 496 samples. Feature vectors were extracted from preprocessed EEG signals, and classification was performed using the RBF kernel. The SVM model achieved a **classification accuracy of 94.96%**, demonstrating high reliability in differentiating between mental states.

Mental State	Precision	Recall	F1-Score	Support
Relaxed or Idle (0)	0.97	0.94	0.95	167
Stressed (1)	0.94	0.91	0.93	167
Concentrated (2)	0.94	1.00	0.97	162
Overall Accuracy			0.95	496

The **macro-average and weighted-average precision, recall, and F1-scores were all 0.95**, indicating consistent model performance across all classes.

Sample Predictions:

- **Input 1** → Predicted Label: 2.0 → Mental State: **Concentrated**
- **Input 2** → Predicted Label: 1.0 → Mental State: **Stressed**
- **Input 3** → Predicted Label: 0.0 → Mental State: **Relaxed or Idle**

These results validate the effectiveness of the SVM model in recognizing and classifying distinct mental states based on EEG signals, supporting its potential for use in real-time brain-computer interface (BCI) applications.

6. CONCLUSION

This project successfully demonstrates the use of machine learning techniques for classifying EEG signals in brain-computer interface (BCI) systems. Starting from data collection and preprocessing to feature extraction and model implementation, each step was carefully designed to ensure accurate and meaningful classification of brain states such as attention and relaxation. Support Vector Machines (SVM) were used as the core classification algorithm due to their robustness and ability to handle non-linear patterns in EEG data using kernel functions. By integrating all components—from signal processing to model prediction—the system offers a reliable framework for interpreting brain activity in real-time. This project highlights the potential of combining neuroscience and machine learning to develop intelligent systems for healthcare, neurofeedback, and assistive technologies.

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