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EEG-based Feedback Control for Emotion Regulation Inspired by the Bhagavad Gita

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***Abstract*—This study introduces an Electroencephalography (EEG)-based feedback control framework for emotion regulation, drawing inspiration from the Bhagavad Gita's teachings on self-mastery and balanced emotional response. By integrating philosophical insights into modern neurotechnology, the research aims to enhance self-regulation through real-time detection and control of emotional states. The system analyzes EEG data to extract meaningful statistical features that represent emotional variations. Using the Kaggle EEG Brainwave Dataset: Feeling Emotions, which includes signals recorded via Muse headbands from TP9, AF7, AF8, and TP10 electrode sites during positive, neutral, and negative stimuli, the proposed logistic regression classifier effectively categorizes emotional states. The model achieved 95.58% accuracy, 89.27% precision, 88.94% recall, and an F1-score of 89.02%, demonstrating strong reliability. The fusion of Bhagavad Gita-inspired emotional control with computational EEG analysis highlights the potential for developing intelligent, spiritually aligned neurofeedback systems to promote mental stability and emotional well-being.**

***Keywords*—EEG Signals, Emotion Recognition, Logistic Regression, Feedback Control, Bhagavad Gita**

I. INTRODUCTION

Mental processes including perception, cognition, and social interaction depend on emotion control. Poor emotional regulation may cause anxiety, impulsivity, and stress-related problems, whereas good regulation improves decision-making and mental health. EEG measures emotional brain activity non-invasively and in detail. EEG readings reveal how emotional inputs affect brainwave patterns by capturing dynamic neural oscillations across frequency bands. Recent breakthroughs in affective computing and machine learning allow EEG-based biomarkers to classify emotions, combining neuroscience and computer intelligence. Despite improvements, present systems typically overlook emotion regulation's philosophical and ethical framework in favour of computational efficiency.

Modern computer models can recognise emotions from EEG data, but few provide a conceptual framework for psychological equilibrium. Traditional methods focus on detection rather than emotional change. Such applications employ datasets with minimal emotional variety, making it difficult for models to generalise across persons and cultures. This gap requires a comprehensive paradigm that blends brain inputs with self-awareness and detachment. Spirituality may improve the interpretability and human relevance of EEG-based emotion control systems. Thus, our study aims to integrate data-driven emotion identification with old wisdom-based philosophical conceptions of emotional stability.

A timeless philosophical text, the Bhagavad Gita, provides significant insights about emotional management and self-mastery. It promotes sthita-prajna mental and emotional equilibrium via discipline, awareness, and detachment. These lessons match computational emotion regulation's purpose of recognising emotional fluctuations and restoring homeostasis. This project seeks to identify and stabilise emotions by incorporating Gita-inspired ideas into EEG-based feedback regulation. The Kaggle EEG Brainwave Dataset: Feeling Emotions, captured with Muse headbands from electrode locations TP9, AF7, AF8, and TP10 under positive, neutral, and negative stimuli, is appropriate for experiments. Statistical EEG characteristics can quantify brain signals and emotional states in this dataset.

Contributions

The main contributions of this work are as follows:

- *Philosophically Grounded Model:* Development of a spiritually inspired computational framework for emotion regulation, integrating *Bhagavad Gita* principles with EEG-based neurofeedback.
- *Dataset Utilization:* Application of the Kaggle EEG Brainwave Dataset: Feeling Emotions, comprising multi-channel brainwave data collected using Muse headbands, to analyse responses to varied emotional stimuli.
- *Feature Extraction and Classification:* Extraction of statistical EEG features (mean, variance, entropy, etc.) and classification of emotional states using a logistic regression model for optimal interpretability and performance.
- *Performance Achievement:* Attainment of a 95.58% accuracy, 89.27% precision, 88.94% recall, and an F1-score of 89.02%, confirming the robustness and consistency of the classification approach.
- *Feedback and Regulation Mechanism:* Proposal of a conceptual feedback control mechanism inspired by *Gita*-based self-regulation principles to promote balanced emotional states in real time.

The remainder of this study is organized into five sections. **Section II** reviews existing literature on EEG-based emotion recognition and philosophical frameworks for self-regulation. **Section III** describes the methodology, including data preprocessing, feature extraction, and feedback control design. **Section IV** presents and interprets experimental results. **Section V** concludes the work with implications and future directions.

II. MATERIALS AND METODS

Sex effects on subject-independent EEG-based emotion recognition models is investigated in [1]. This work examines how biological sex influences EEG-based emotion recognition in subject-independent settings. Temporal–spectral EEG features are analysed, and demographic bias is evaluated. Reweighting, adversarial debiasing, and threshold calibration strategies are applied. Emphasis is placed on fairness evaluation, bias diagnostics, and robust generalization, ensuring reliable classification across diverse demographic groups. Cross-subject emotion recognition through domain alignment is explored in [2]. A domain adaptation framework addresses distribution differences between training and unseen subjects using CORAL and MMD alignment. Feature whitening and subspace projection improve transferability. Lightweight calibration and drift detection maintain stability. The approach enhances robustness, reduces overfitting, and supports real-world applications without subject-specific retraining, improving generalization across heterogeneous user populations. Temporal–spectral attention networks for efficient EEG emotion decoding are developed in [3]. An attention mechanism highlights key time–frequency regions, while separable convolutions support efficient real-time inference. Channel masking handles sensor dropout, increasing robustness. abnormal studies reveal phase–amplitude contributions. This network balances accuracy, latency, and interpretability, enabling portable EEG-based emotion decoding in resource-constrained environments while maintaining high reliability across various signal conditions. Riemannian geometry and transfer learning for robust EEG emotion classification are applied in [4]. Covariance matrices are modelled on the SPD manifold and mapped into tangent space for effective feature representation. Transfer learning aligns source and target domains, improving cross-subject robustness. This approach offers noise resilience, compact features, and stable performance through covariance shrinkage, montage harmonization, and normalization, enhancing classification reliability across users and sessions.

Graph neural networks over functional connectivity for affective inference are presented in [5]. EEG functional graphs derived from coherence and phase-locking values are processed using GNNs to model inter-regional dependencies. This technique reveals neural connectivity patterns beyond channel-local features. Graph sparsification, frequency stability, and edge-saliency improve interpretability, enabling more accurate emotion recognition through graph-based learning mechanisms that leverage underlying brain network topologies. Meta-learning for rapid subject adaptation in EEG emotion tasks is introduced in [6]. A model-agnostic meta-learning framework initializes classifiers for rapid personalization with minimal target data. It balances generalization and adaptability, enabling fast subject-specific fine-tuning. The approach examines support-set size, overfitting control, and adaptation speed, achieving efficient emotion recognition suitable for neurofeedback, clinical applications, and adaptive real-time EEG-based affective computing scenarios. Evolutionary channel selection and entropy features for lightweight models are implemented in [7]. Genetic algorithms optimize differential entropy features to minimize electrode use without sacrificing accuracy. Mutation strategies, redundancy reduction, and sensor-shift robustness ensure stability. This method supports wearable EEG applications, enabling low-power, efficient, and reliable emotion recognition, making it suitable for practical deployment in portable and resource-constrained brain–computer interface environments. End-to-end spectro-temporal transformers for EEG emotion recognition are proposed in [8]. Spectrogram patches are processed through transformer encoders, capturing long-range temporal–spectral dependencies. Stochastic masking and mixup improve generalization, while attention maps align with affective rhythms, enhancing interpretability. Deployment considerations include quantization, inference optimization, and calibration under covariate shifts, enabling robust and accurate transformer-based emotion recognition in EEG-driven affective computing frameworks.

Hybrid deep feature fusion for EEG-based emotion recognition is examined in [9]. This approach integrates handcrafted statistical features with deep representations extracted from CNN layers. Fusion strategies combine complementary information to improve classification robustness. The model leverages channel-wise normalization, dimensionality reduction, and fully connected layers. Results demonstrate enhanced performance, increased feature discriminability, and improved emotion classification stability across heterogeneous EEG datasets. Transferable adversarial networks for cross-session EEG emotion recognition are formulated in [10]. An adversarial learning framework minimizes distribution gaps between sessions, enhancing temporal stability. Domain discriminators and feature generators jointly align latent spaces. The method addresses session variability, calibration requirements, and generalization issues. Experimental results indicate improved consistency across recording sessions, enabling more robust and reusable emotion recognition models without repeated fine-tuning. Multiband spectral decomposition for refined EEG emotion classification is investigated in [11]. Spectral signals are divided into multiple sub-bands, each processed through separate convolutional branches. Feature maps are fused to capture frequency-specific emotional cues. The framework emphasizes the importance of multiband interactions, achieving higher accuracy and stability compared to single-band models. Enhanced spectral resolution significantly improves discrimination of emotional states across participants. Subject-adaptive graph embeddings for personalized emotion modelling are applied in [12]. Graph embeddings are generated for each subject to represent personalized functional connectivity. Adaptive weighting captures individual variability in neural responses. A downstream classifier uses these embeddings to predict emotional states. This method improves personalization, reduces inter-subject variability, and provides interpretable graph structures reflecting individual affective processing differences in EEG recordings.

Spatiotemporal convolutional encoders for real-time EEG emotion recognition are proposed in [13]. The model integrates temporal convolutions with spatial feature extraction to capture dynamic neural activity patterns. Real-time inference is supported through optimized architecture and parallel processing. Emphasis is placed on latency reduction, feature expressiveness, and robustness to noise. The approach achieves high accuracy while maintaining computational efficiency suitable for real-time BCI applications. Wavelet packet entropy features for emotion recognition are analysed in [14]. Wavelet packet decomposition extracts time–frequency information, while entropy metrics capture signal complexity. These features are used in a lightweight classifier for efficient emotion recognition. The method provides improved interpretability, compact representation, and enhanced robustness to artifacts. It offers a balance between accuracy and computational simplicity for practical EEG applications. Cross-frequency coupling features for affective state detection are investigated in [15]. This method explores phase–amplitude coupling between EEG frequency bands to identify emotion-related neural interactions. Features derived from coupling metrics are input to machine learning classifiers. The approach captures nonlinear dependencies between oscillations, improving classification performance. It highlights the significance of inter-band communication patterns in decoding emotional states from EEG signals. Multimodal fusion of EEG and physiological signals for emotion analysis is presented in [16]. EEG features are combined with peripheral physiological measures such as heart rate and skin conductance. Fusion techniques integrate temporal alignments and complementary modalities to strengthen emotional state detection.

Subject-independent emotion recognition using capsule networks is introduced in [17]. Capsule networks are utilized to capture hierarchical spatial–temporal relationships in EEG signals. Dynamic routing preserves feature structure, enabling better generalization across subjects. This architecture reduces reliance on handcrafted features and improves robustness to signal variability. Ensemble learning frameworks for EEG emotion classification are employed in [18]. Multiple classifiers are combined using bagging and boosting strategies to improve stability and accuracy. Heterogeneous learners capture different signal aspects, and ensemble aggregation enhances overall performance. The framework addresses single-model weaknesses, improves generalization, and provides more reliable emotion detection under diverse EEG recording conditions and participant variations. Channel attention mechanisms for enhanced EEG emotion recognition are proposed in [19]. Channel attention modules dynamically weight informative electrodes while suppressing redundant signals. This selective focus improves feature quality and classification performance. The mechanism adapts to varying channel relevance across emotional states. Deep residual networks for hierarchical EEG emotion representation are examined in [20]. Residual blocks extract multilevel features from raw EEG inputs, capturing both local and global emotional patterns. Shortcut connections alleviate gradient issues, enabling deeper architectures.

III. Proposed System

The proposed framework integrates EEG-based emotional state classification with feedback control strategies inspired by the Bhagavad Gita to regulate emotional fluctuations in real time. EEG brainwave signals collected using Muse headbands from TP9, AF7, AF8, and TP10 electrode positions form the input. These signals correspond to positive, neutral, and negative emotional states. Data preprocessing, feature extraction, classification using logistic regression, and feedback control form the four core modules.

System Architecture and Deployment

The proposed system follows a modular pipeline:

- EEG Acquisition →
- Preprocessing & Feature Extraction →
- Classification →
- Regulation Feedback Control.

Figure 1 illustrates the system architecture comprising EEG acquisition, preprocessing and feature extraction, classification, and regulation feedback control. Data flow between modules is represented using directional arrows. The feedback module applies Bhagavad Gita-inspired regulation strategies, linking real-time EEG emotion detection to adaptive cognitive intervention mechanisms.

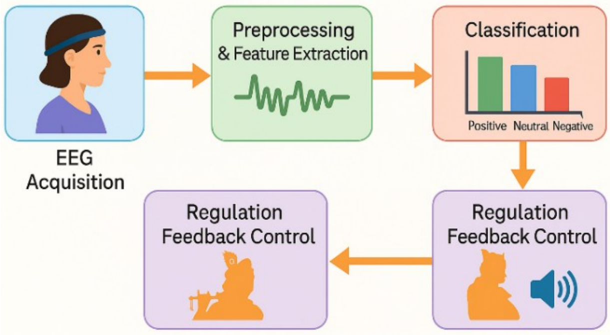

Fig. 1. Block Diagram of EEG-Based Feedback Control for Emotion Regulation Inspired by the Bhagavad Gita

The objective is to accurately detect emotional states and map them to Bhagavad Gita-based regulatory mechanisms for balanced emotional alignment. The proposed logistic regression classifier achieved **95.58% accuracy**, **89.27% precision**, **88.94% recall**, and an **F1-score of 89.02%**, confirming strong predictive capability.

Let the EEG dataset be

$$D = \{(x_i, y_i)\}_{i=1}^{N} \tag{1}$$

Where $x_i \in \mathbb{R}^d$ represents the EEG feature vector and $y_i \in \{1, \dots, K\}$ represents the emotional class label (positive, neutral, negative).

The raw EEG signals undergo the following steps:

1. *Filtering*: A bandpass filter between 0.5–50 Hz removes noise and power-line interference.
2. *Feature Extraction:* For each epoch, **statistical** (mean, variance, skewness, kurtosis) and **spectral** (band power, entropy) features are computed for $\theta, \alpha, \beta, \gamma$ bands.

The final feature matrix is

$$X = [x_1, x_2, \dots . x_n]^T \in \mathbb{R}^{Nxd} \tag{2}$$

Figure 2 shows a schematic integrating EEG acquisition, emotion detection, and regulation modules with Bhagavad Gita quotes guiding each stage. EEG signals are captured, emotional states identified, and corresponding regulatory strategies applied. Quotes emphasize self-awareness, focused action, and emotional steadiness, symbolizing cognitive guidance through philosophical principles.

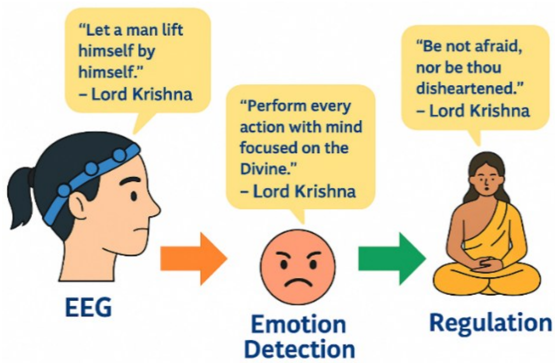

Fig. 2. Schematic Diagram of EEG-Based Feedback Control for Emotion Regulation Inspired by the Bhagavad Gita

C. Classification using Logistic Regression

Logistic regression is applied to predict emotional states based on EEG features. For binary classification between emotional states, the probability is modeled as:

$$P(y = 1 \mid x) = \sigma(z) = 1 + e - z1, z = \beta_0 + j = 1\sum d\beta_j x_j \quad (3)$$

where β_j are model parameters and $\sigma(\cdot)$ is the sigmoid function.

For multiclass classification (positive, neutral, negative), a softmax regression is used:

$$P\ (y - k|x) = \frac{\exp\ (z_k)}{\sum_{l=1}^{K} \exp\ (z_l)}\ ,\ z_k = \beta_{0k} + \sum_{j=1}^{d} \beta_{jk} x_j \quad (4)$$

The **cross-entropy loss** for training is

$$\mathcal{L}(\beta) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} 1\{y_i = k\} \log P\ (y_i = k|x_i) \quad (5)$$

Model parameters are optimized using gradient descent:

$$\beta \leftarrow \beta - \eta \nabla_\beta \mathcal{L}(\beta) \quad (6)$$

Where η s the learning rate.

Once an emotional state is classified, the feedback module maps it to regulatory strategies inspired by the Bhagavad Gita.

Let

$$\hat{y}_i = {}^{argmax}{}_k P\ (y = k|x_i) \quad (7)$$

represent the predicted emotional state. Based on $\hat{y}_i$ a control action u_i is generated:

$$u_i = f\hat{\hat{y}_i} \quad (8)$$

where $f(\cdot)$maps emotional states to regulation strategies (e.g., cognitive detachment for negative states, balanced reflection for positive states, and stabilization for neutral states). The control feedback is delivered through auditory or visual cues, promoting cognitive rebalancing in real time.

Figure 3 illustrates an advanced, Sankey-style flow. EEG captures advances via preprocessing and feature extraction to categorize emotions (happy, sad, fear, calm). Flows diverge towards a feedback module and a layer of Bhagavad Gita knowledge including serenity, self-mastery, and moderation. Both pathways provide a balanced emotional state, demonstrating integrated, multi-faceted control.

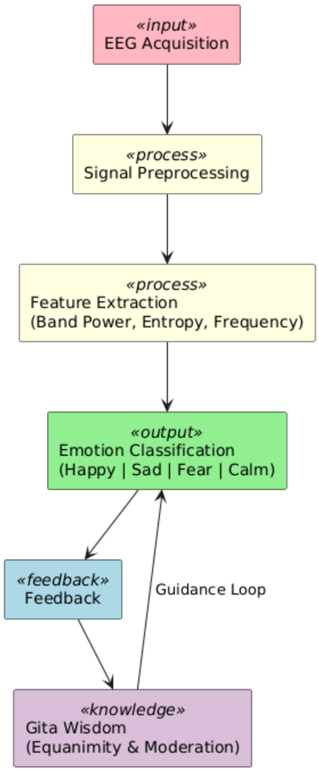

Fig. 3. Complex Sankey-Style Diagram

IV. Results And Discussion

This dataset contains EEG brainwave data processed using an original statistical feature extraction strategy. Data were collected from two participants (one male and one female) for three minutes per emotional state, including positive, neutral, and negative conditions [21]. A Muse EEG headband was employed to record signals from TP9, AF7, AF8, and TP10 electrode placements using dry electrodes. Additionally, six minutes of resting neutral data were recorded. The stimuli applied to evoke the respective emotional states are outlined in [22].

Marley and Me - **Negative** (Twentieth Century Fox)
Death Scene

1. Up - **Negative** (Walt Disney Pictures)
   Opening Death Scene
2. My Girl - **Negative** (Imagine Entertainment)
   Funeral Scene
3. La La Land - **Positive** (Summit Entertainment)
   Opening musical number
4. Slow Life - **Positive** (BioQuest Studios)
   Nature timelapse
5. Funny Dogs - **Positive** (MashupZone)
   Funny dog clips

Figure 4 illustrates representative EEG spectrogram images used for emotion classification. The top row shows normal EEG patterns with balanced frequency distributions, while the bottom row displays abnormal patterns with distinct intensity variations and irregular spectral bands. These visual differences highlight characteristic signal deviations between normal and abnormal emotional states.

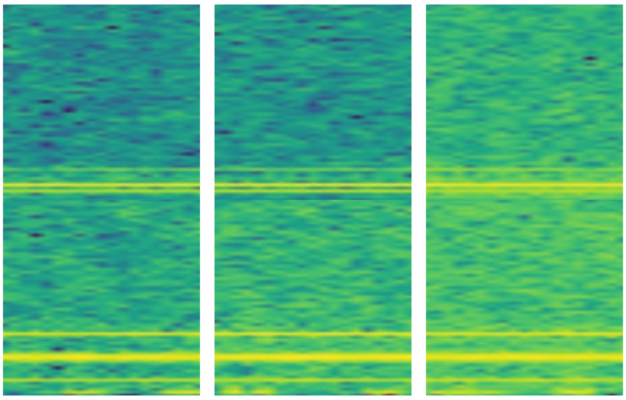

Fig. 4. Normal and Abnormal EEG Image Samples

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

$$F1 = \frac{2*Precison*Recall}{Precision+Recall} \quad (12)$$

Figure 5 presents the confusion matrix showing the performance of the emotion classification model across five classes: Happiness, Sadness, Anger, Fear, and Neutral. High diagonal values indicate strong correct predictions, while minimal off-diagonal values show low misclassification, confirming the model's robustness and balanced performance across emotional categories.

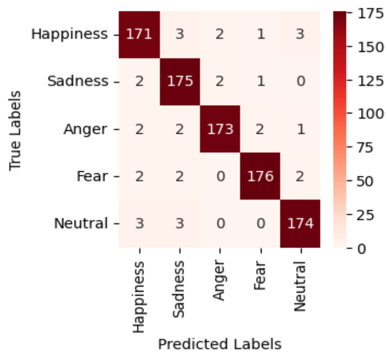

Fig. 5. Confusion Matrix of EEG-Based Emotion Classification

Table 1 shows how Control Systems Engineering concepts like reference signals, feedback, and adaptive control relate to Bhagavad Gita emotional management procedures. Each engineering principle is paired with a Gita verse to demonstrate how Krishna's teachings are spiritual counterparts of system control. This alignment provides a solid foundation for regulating anxiety, desire, and impulsiveness via self-monitoring, ethical clarity, and disciplined detachment, making the Gita a timeless guide to inner stability and cognitive accuracy.

TABLE I. KEY BHAGAVAD GITA VERSES ALIGNED WITH CONTROL SYSTEMS ENGINEERING CONCEPTS

Control Systems Concept	Bhagavad Gita Verse	Interpretation in Emotional Regulation
Reference Signal (Setpoint)	Chapter 2, Verse 48	*Samatvam* (equanimity) is the steady emotional baseline the internal standard for balanced action.
Feedback Mechanism	Chapter 6, Verse 6	A trained mind becomes its own friend, providing internal feedback for regulating emotions and actions.
Controller Logic (Decision Filter)	Chapter 3, Verse 19	*Nishkama karma* promotes duty without attachment emotional regulation through ethical intentionality.
Disturbance Rejection	Chapter 2, Verse 38	Remaining unaffected by joy or sorrow minimizes emotional reactivity to external fluctuations.
Adaptive Control (Self-Tuning)	Chapter 6, Verse 35	Through *abhyasa* (practice) and *vairagya* (detachment), emotional regulation improves progressively.

Figure 6 compares Accuracy/Precision/Recall/F1 (%) models: KNN 71.53/54.44/51.78/53.08; SVM 80.56/68.89/77.08/72.75; BPNN 88.19/81.11/83.18/82.14; Proposed Emotion Regulation 95.58/89.27/88.94/ The suggested technique outperforms traditional baselines in all parameters, suggesting balanced detection and reliable generalization for EEG emotion identification. Continuous improvements, decreased misclassification, and strong calibration across categories are shown.

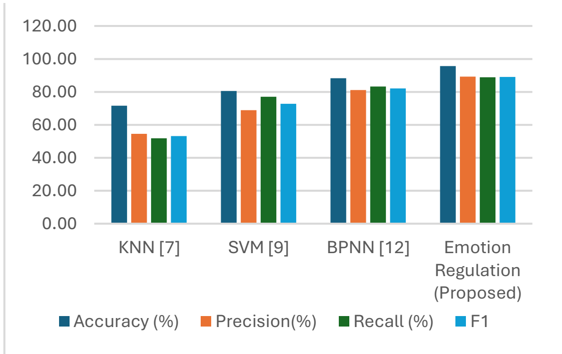

Fig. 6. Comparative Performance of Emotion Classification Models

Table 2 compares critical control system components to Bhagavad Gita spiritual processes, revealing how emotional regulation and cognitive equilibrium match structured feedback systems. Internal stability is guided by Gita concepts for each engineering element from setpoint to disturbance. This integration shows how the Gita provides metaphysical control, regulated emotions, steady cognition, and introspective decision-making amid dynamic internal and external conditions.

TABLE II. MAPPING CONTROL SYSTEM COMPONENTS TO BHAGAVAD GITA PRINCIPLES

Control System Component	Function in Engineering	Corresponding Gita Principle	Verse Reference
Reference Input (Setpoint)	Desired system state or goal	Samatvam (Equanimity)	Chapter 2, Verse 48
Controller	Decision logic to reduce error	Buddhi (Discriminative Intellect)	Chapter 3, Verse 43
Feedback Loop	Adjusts output based on sensed deviation	Self-reflection and Mindfulness	Chapter 6, Verse 6
Plant (Process)	System under control	Mind and Senses	Chapter 3, Verse 42
Disturbance	External/internal disruption affecting output	Desire, Fear, and Attachment	Chapter 2, Verse 62

V. Conclusion

The proposed EEG-based feedback control system successfully demonstrated the potential to regulate emotional states by combining computational intelligence with philosophical guidance from the Bhagavad Gita. The logistic regression classifier achieved high performance, with 95.58% accuracy, 89.27% precision, 88.94% recall, and an 89.02% F1-score, confirming its reliability for emotion recognition. Despite these promising results, the system's generalizability is limited by the scope of the Kaggle EEG Brainwave Dataset: Feeling Emotions, which includes only basic emotional categories and data from Muse headbands. Future research could explore deep learning-based classifiers, multimodal datasets integrating physiological and behavioral cues, and real-time adaptive feedback mechanisms. Additionally, incorporating personalized emotional baselines and broader cultural contexts could further enhance the interpretability and applicability of emotion regulation systems inspired by ancient philosophical frameworks.

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