Event Analysis of Functional Near-Infrared Spectroscopy Brain Signals Using Machine Learning and Generative Adversarial Networks

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***Abstract*—The analysis of brain signals using machine learning and deep learning techniques has demonstrated considerable promise for diagnosing neurological disorders and developing brain-computer interfaces. This paper presents a comprehensive comparative study of machine learning algorithms and Generative Adversarial Networks (GANs) for event analysis of functional near-infrared spectroscopy (fNIRS) signals during cognitive and motor tasks. Eight subjects were evaluated using multiple classification algorithms including Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), XGBoost, Decision Trees, Random Forest, Multilayer Perceptron (MLP), and AdaBoost. Statistical features including mean, variance, slope, peak, kurtosis, and skewness were extracted from preprocessed fNIRS data. Experimental results demonstrate that XGBoost achieved the highest classification accuracy of 91.43% for Subject 2, while Light Gradient Boosting Machine (LGBM) consistently performed well across subjects with accuracies ranging from 75.7% to 90.08%. Additionally, a GAN-based approach was implemented for synthetic fNIRS data generation, achieving balanced generator and discriminator losses after 100 training epochs. The findings suggest that ensemble methods, particularly gradient boosting algorithms, are highly effective for fNIRS signal classification, while GANs offer promising potential for data augmentation in scenarios with limited training samples.**

***Index Terms*—Functional Near-Infrared Spectroscopy, fNIRS, Brain-Computer Interface, Machine Learning, Deep Learning, Generative Adversarial Networks, XGBoost, Signal Classification, Cognitive Neuroscience**

I. Introduction

The study of brain signals using computational techniques has emerged as a critical research area for understanding cognitive processes, diagnosing neurological disorders, and developing brain-computer interfaces (BCIs). Functional near-infrared spectroscopy (fNIRS) has gained significant attention as a non-invasive neuroimaging modality that measures changes in cerebral blood oxygenation levels in response to neural activity [1]. Unlike electroencephalography (EEG), fNIRS offers improved spatial resolution and reduced susceptibility to motion artifacts, making it particularly suitable for naturalistic experimental paradigms.

Event-related analysis of brain signals has grown in popularity as researchers seek to predict and categorize various cognitive and motor activities, including attention tasks, memory recall, and seizure onset detection [2]. Machine learning and deep learning techniques have demonstrated remarkable success in extracting meaningful patterns from complex neuroimaging data, enabling automated classification of brain states with high accuracy.

However, existing EEG-based analysis systems utilizing machine learning may have limited applicability to fNIRS signals due to fundamental differences in signal characteristics. fNIRS signals exhibit a relatively delayed and dispersed hemodynamic response compared to the rapid electrical signals captured by EEG, necessitating specialized analytical approaches [3].

A significant challenge in brain signal analysis is the reliance on labeled training data. Obtaining accurately annotated data for rare neurological events is time-consuming and expensive, while inter-observer variability in labeling can limit model generalizability. Generative Adversarial Networks (GANs) offer a promising solution by generating synthetic data that augments limited training samples [8].

This paper presents a comprehensive evaluation framework addressing the following objectives:

- Systematic comparison of multiple machine learning algorithms for fNIRS signal classification across eight subjects
- Extraction and evaluation of statistical features including central tendency, dispersion, and shape characteristics
- Implementation and assessment of GANs for synthetic fNIRS data generation
- Analysis of algorithm performance variability across individual subjects

The remainder of this paper is organized as follows: Section II reviews related work in brain signal analysis. Section III details the theoretical background of machine learning algorithms and GANs. Section IV presents the methodology including data collection, preprocessing, and model implementation. Section V reports experimental results, and Section VI concludes with discussion and future directions.

II. Related Work

A. EEG and fNIRS-Based Brain-Computer Interfaces

Lotte et al. [2] provided a comprehensive review of classification algorithms for EEG-based BCIs, discussing linear discriminant analysis, support vector machines, and artificial neural networks. Their work established foundational benchmarks for brain signal classification performance.

Abdalmalak et al. [3] explored fNIRS for single-session communication with locked-in patients, demonstrating the modality's potential for BCI applications. Machine learning algorithms successfully classified fNIRS signals corresponding to imagined tasks, enabling binary communication.

B. Machine Learning for Brain Signal Classification

Abadi and Ghasemi [4] investigated machine learning algorithms for classifying EEG signals during mental tasks including relaxation, arithmetic, and imagination. Support vector machines achieved 95.83% accuracy, outperforming k-nearest neighbors and artificial neural networks.

Hramov et al. [5] demonstrated fNIRS classification for motor-related brain activity, achieving high accuracy in distinguishing right- and left-hand motor imagery using LDA and SVM classifiers.

C. Deep Learning Approaches

Guler and Ubeyli [6] reviewed deep learning for EEG signal classification, covering convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures. Deep learning models demonstrated superior performance for emotion recognition, seizure detection, and sleep stage classification.

Yang and Hong [7] combined fNIRS with deep learning for mild cognitive impairment detection, achieving 86.7% accuracy using resting-state data from 72 subjects.

D. Generative Adversarial Networks for Brain Signals

Goodfellow et al. [8] introduced GANs, establishing the adversarial training framework between generator and discriminator networks. Wu et al. [9] applied GANs for EEG data generation and augmentation, demonstrating improved classifier accuracy for P300-based speller systems.

III. Background and Theory

A. Machine Learning Fundamentals

Machine learning enables computers to learn patterns from data without explicit programming. The fundamental components include supervised learning (classification and regression with labeled data), unsupervised learning (pattern discovery in unlabeled data), and reinforcement learning (learning through environmental feedback).

1) Statistical Features: Feature extraction transforms raw signals into discriminative representations. Key statistical features employed in this study include:

Central Tendency Features: Mean, median, and mode characterize the central value of signal distributions. The arithmetic mean is computed as:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

Dispersion Features: Variance and standard deviation quantify signal spread:

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \tag{2}$$

Shape Features: Skewness measures distribution asymmetry, while kurtosis quantifies peaked-ness relative to a normal distribution.

2) Classification Algorithms: **Linear Discriminant Analysis (LDA)** identifies optimal linear combinations of features to maximize class separation while minimizing within-class variance.

K-Nearest Neighbors (KNN) classifies samples based on majority voting among the k closest training examples in feature space.

XGBoost employs gradient boosting to combine weak learners into a strong classifier, with regularization to prevent overfitting.

Random Forest aggregates predictions from multiple decision trees trained on random data subsets, improving generalization through ensemble averaging.

Multilayer Perceptron (MLP) consists of interconnected neurons organized in layers, applying non-linear transformations to capture complex input-output relationships.

B. Generative Adversarial Networks

GANs comprise two neural networks trained adversarially: a generator G that synthesizes samples from random noise, and a discriminator D that distinguishes real from generated samples. Fig. 1 illustrates the GAN architecture.

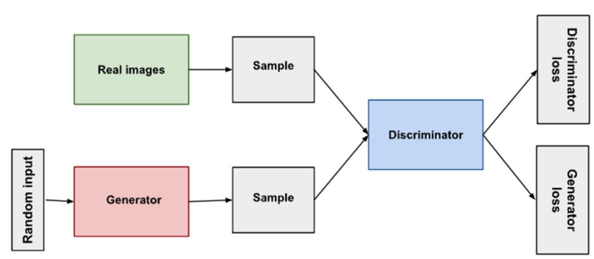

Fig. 1. Overview of Generative Adversarial Network (GAN) architecture showing the generator and discriminator networks in adversarial training configuration.

The training objective is formulated as a minimax game:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}}[\log D(x)] + \mathbb{E}_{z\sim p_z}[\log(1-D(G(z)))] \tag{3}$$

where p_{data} represents the true data distribution and p_z is the prior noise distribution.

C. Discriminative vs. Generative Models

Fig. 2 illustrates the fundamental difference between discriminative and generative modeling approaches.

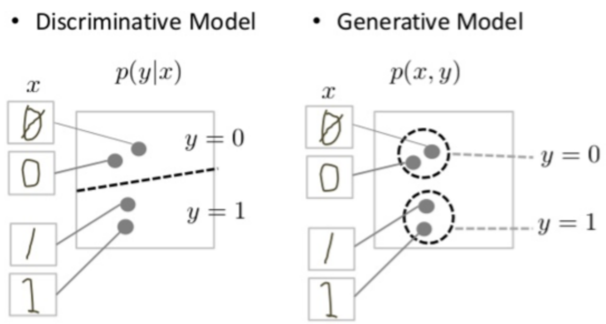

Fig. 2. Comparison of discriminative and generative models. Discriminative models learn decision boundaries (p(Y—X)), while generative models learn the underlying data distribution (p(X,Y)).

D. GAN Training Process

The discriminator is trained using backpropagation to minimize classification error between real and synthetic samples, as shown in Fig. 3.

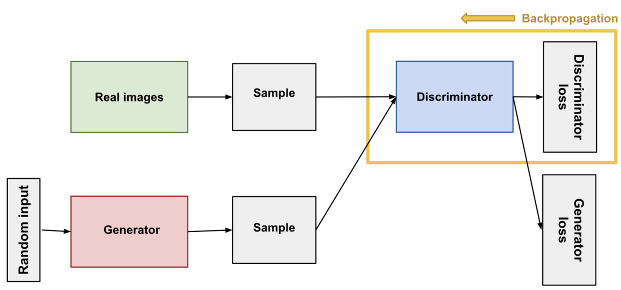

Fig. 3. Backpropagation in discriminator training. The discriminator learns to distinguish real samples from generator outputs by minimizing binary cross-entropy loss.

The generator is trained to maximize the discriminator's error, as illustrated in Fig. 4.

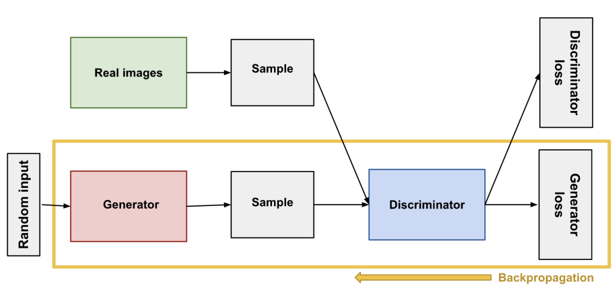

Fig. 4. Backpropagation in generator training. The generator learns to produce realistic samples by maximizing the discriminator's misclassification rate.

IV. Methodology

A. Data Collection

Fig. 5 presents the schematic illustration of the fNIRS signal analysis pipeline employed in this study.

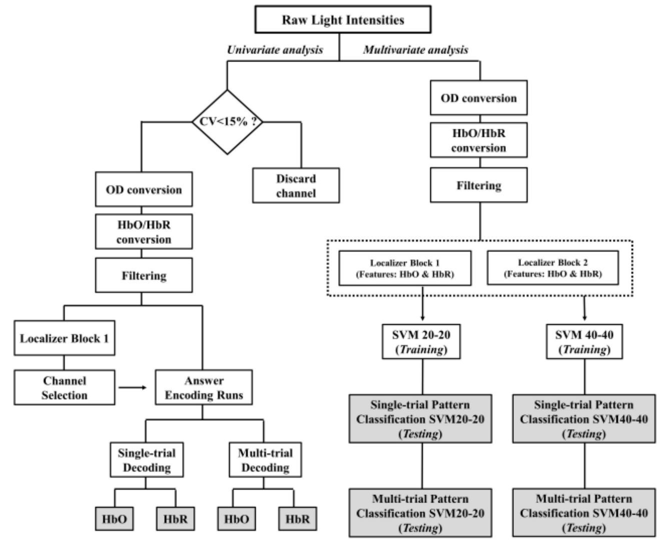

Fig. 5. Schematic illustration of fNIRS signal analysis pipeline showing univariate and multivariate analysis pathways. OD: optical density; CV: coefficient of variation; HbO: oxygenated hemoglobin; HbR: deoxygenated hemoglobin.

fNIRS data was collected using a configuration of three source optodes and six detector optodes positioned according to the international 10-20 EEG system, as shown in Fig. 6. This configuration enabled measurement of hemoglobin concentration changes at specific brain locations with spatial resolution determined by source-detector separation distance.

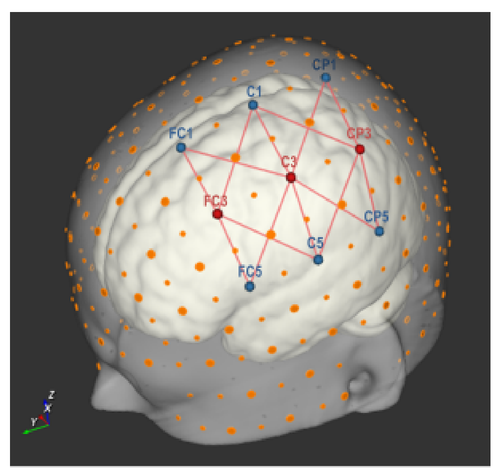

Fig. 6. Optode configuration showing nine sites containing three source optodes and six detecting optodes according to the international 10-20 EEG system. Red lines represent 14 source-detector channel pairs.

The experimental paradigm involved cognitive tasks designed to elicit measurable hemodynamic responses in the prefrontal cortex. Eight subjects participated in the study, with data recorded during task performance.

B. Data Preprocessing

Raw fNIRS signals underwent preprocessing to remove noise and artifacts, as illustrated in Fig. 7.

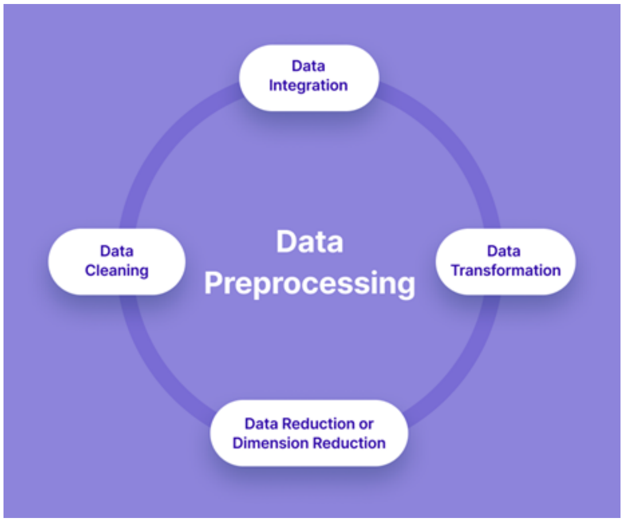

Fig. 7. Flow diagram of data preprocessing pipeline including filtering, baseline correction, and artifact removal stages.

Filtering: Bandpass filtering eliminated low-frequency drifts and high-frequency noise components.

Baseline Correction: Mean or median values from pre-task intervals were subtracted to remove baseline drift.

Artifact Removal: Wavelet-based denoising and independent component analysis (ICA) addressed motion artifacts, physiological noise, and instrumental artifacts.

Following preprocessing, the modified Beer-Lambert law was applied to convert optical density changes to oxy-hemoglobin (HbO) and deoxy-hemoglobin (HbR) concentration changes.

C. Feature Extraction

Six statistical features were extracted from preprocessed fNIRS signals:

1) **Mean:** Average signal amplitude
2) **Variance:** Signal dispersion measure
3) **Slope:** Linear trend coefficient
4) **Peak:** Maximum amplitude value
5) **Kurtosis:** Distribution peaked-ness
6) **Skewness:** Distribution asymmetry

Principal Component Analysis (PCA) was applied for dimensionality reduction while preserving discriminative information.

D. Machine Learning Model Implementation

Eight classification algorithms were implemented and evaluated:

Data was split into training (80%) and testing (20%) sets. K-fold cross-validation (k=5) was employed to estimate generalization performance and optimize hyperparameters.

E. GAN Implementation

The GAN algorithm for fNIRS data generation is illustrated in Fig. 8.

The GAN architecture comprised:

TABLE I
MACHINE LEARNING ALGORITHM CONFIGURATIONS

Algorithm	Key Parameters
LDA	Default solver
KNN	k optimized via cross-validation
LGBM	100 estimators, learning rate 0.1
XGBoost	100 estimators, max depth 6
Decision Tree	Gini impurity criterion
Random Forest	100 trees, bootstrap sampling
MLP	2 hidden layers, ReLU activation
AdaBoost	50 estimators, SAMME.R

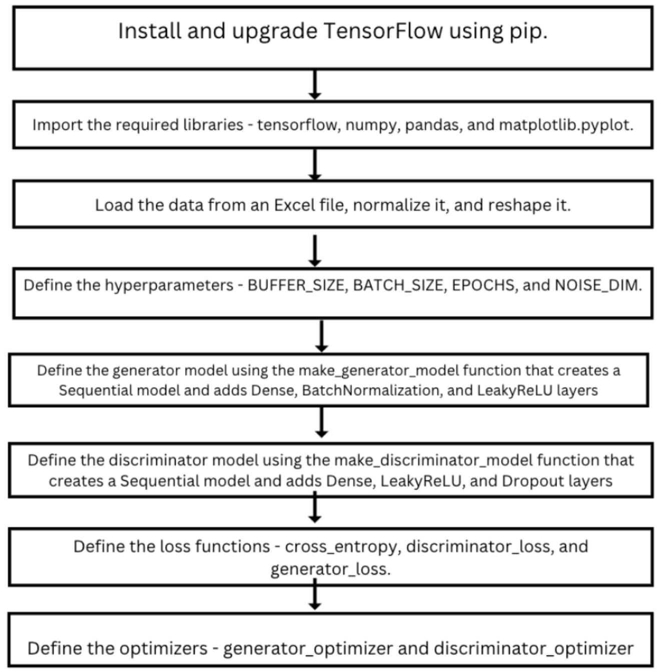

Fig. 8. Algorithm flowchart for Generative Adversarial Network (GAN) implementation for fNIRS data generation, showing generator and discriminator training loops.

Generator Network: Sequential model with Dense layers, Batch Normalization, and LeakyReLU activations. Input: noise vector of dimension NOISE_DIM. Output: synthetic fNIRS feature vectors.

Discriminator Network: Sequential model with Dense layers, LeakyReLU activations, and Dropout for regularization. Output: probability of input being real.

Training hyperparameters:

- BUFFER_SIZE: Dataset size for shuffling
- BATCH_SIZE: 32 samples per iteration
- EPOCHS: 100 training iterations
- NOISE_DIM: 100-dimensional latent space

Binary cross-entropy loss was used for both networks, with Adam optimizer for gradient descent.

V. Experimental Results

A. Machine Learning Classification Performance

Table II presents classification accuracy for all algorithms across eight subjects.

TABLE II
CLASSIFICATION ACCURACY (%) ACROSS SUBJECTS

Algorithm	S1	S2	S3	S4	S5	S6	S7	S8
LDA	76.4	84.3	84.4	53.3	81.3	78.9	79.0	76.1
KNN	65.5	72.7	73.2	58.2	72.4	70.3	73.1	66.8
LGBM	82.0	85.2	90.1	75.7	86.8	85.2	85.0	84.4
XGBoost	**82.7**	**91.4**	89.9	73.6	86.0	84.4	83.9	84.0
Decision Tree	79.5	86.3	87.0	67.8	80.6	84.4	78.4	80.6
Random Forest	72.9	86.6	85.3	66.3	77.8	77.7	78.5	75.4
MLP	79.1	84.3	86.0	65.7	81.1	80.5	80.6	78.5
AdaBoost	65.7	52.4	78.0	55.1	70.5	68.1	63.3	64.1

1) Best Performing Algorithms: XGBoost achieved the highest accuracy of 91.43% for Subject 2, demonstrating superior performance for gradient boosting approaches. LGBM consistently ranked among the top performers across all subjects, with accuracies ranging from 75.7% (Subject 4) to 90.1% (Subject 3).

Fig. 9 and Fig. 10 present visual comparisons of algorithm performance for Subjects 1 and 2.

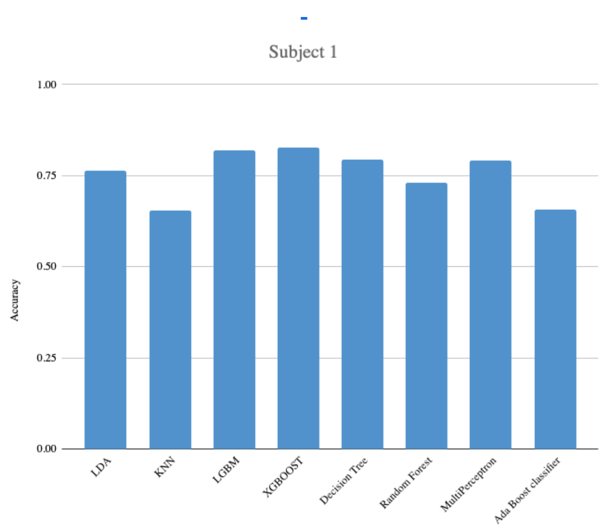

Fig. 9. Classification accuracy comparison across algorithms for Subject 1. XGBoost (82.7%) and LGBM (82.0%) achieved the highest accuracies.

2) Subject-Specific Variability: Significant inter-subject variability was observed. Subject 4 exhibited the lowest overall accuracies (maximum 75.7%), suggesting more complex or noisy data characteristics. Subjects 2 and 3 achieved the highest accuracies across multiple algorithms, indicating cleaner signal quality or more discriminative hemodynamic responses.

3) Algorithm Comparison: Table III summarizes average performance across subjects.

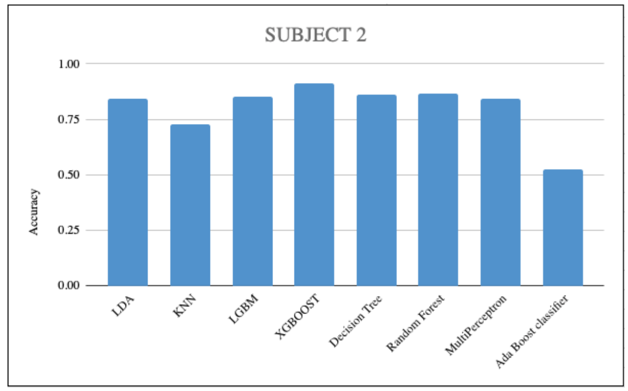

Fig. 10. Classification accuracy comparison across algorithms for Subject 2. XGBoost achieved the study's highest accuracy of 91.43%.

TABLE III
AVERAGE CLASSIFICATION ACCURACY ACROSS ALL SUBJECTS

Algorithm	Mean Accuracy (%)	Std Dev
XGBoost	84.49	5.52
LGBM	84.30	4.21
Decision Tree	80.58	6.08
MLP	79.48	6.12
LDA	76.71	9.45
Random Forest	77.56	6.48
KNN	69.03	5.23
AdaBoost	64.65	7.89

Gradient boosting methods (XGBoost, LGBM) demonstrated superior and consistent performance. AdaBoost exhibited the poorest performance, particularly for Subject 2 (52.4%), indicating sensitivity to data characteristics.

B. Feature Combination Analysis

Linear Discriminant Analysis was applied to evaluate discriminative power of feature pairs. Table IV presents selected results.

TABLE IV
LDA ACCURACY (%) FOR FEATURE COMBINATIONS

Feature Pair	S1	S2	S3
Mean-Slope	74.0	76.3	83.5
Var-Slope	74.9	75.5	81.0
Slope-Peak	74.4	77.5	82.6
Slope-Kurtosis	73.3	76.3	82.4
Mean-Peak	58.8	73.3	69.6
Peak-Kurtosis	58.1	67.8	70.8

Slope-related feature combinations (Mean-Slope, Var-Slope, Slope-Peak) consistently achieved higher classification accuracy compared to other pairings, suggesting temporal dynamics carry significant discriminative information for fNIRS signals.

C. GAN Training Results

Table V presents generator and discriminator losses during GAN training.

TABLE V
GAN TRAINING LOSS EVOLUTION

Epoch	Generator Loss	Discriminator Loss
10	1.021	1.221
20	0.967	1.189
30	1.154	1.252
40	1.098	1.100
50	1.048	1.174
60	0.856	1.223
70	1.306	0.898
80	1.038	1.227
90	1.110	0.997
100	1.088	1.089

Fig. 11 visualizes the GAN training dynamics over 100 epochs.

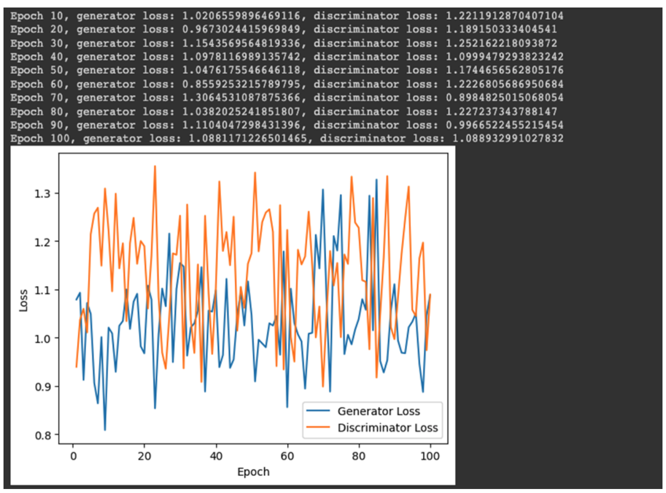

Fig. 11. Generator and discriminator loss curves during GAN training. Convergence to approximately equal losses (1.088 vs 1.089) at epoch 100 indicates successful adversarial equilibrium.

At epoch 100, generator and discriminator losses converged to approximately equal values (1.088 and 1.089), indicating successful adversarial equilibrium. The generator learned to produce samples sufficiently realistic to challenge the discriminator, while the discriminator maintained ability to distinguish real from synthetic samples.

Loss fluctuations at epochs 30 and 70 suggest temporary training instability, a common phenomenon in GAN training that was resolved through continued optimization.

VI. DISCUSSION

A. Algorithm Performance Analysis

The experimental results demonstrate that gradient boosting ensemble methods, particularly XGBoost and LGBM, consistently outperform other algorithms for fNIRS signal classification. This superiority can be attributed to several factors:

1) **Handling of Feature Interactions:** Gradient boosting captures complex non-linear relationships between statistical features that linear methods (LDA) cannot model.
2) **Robustness to Noise:** Ensemble averaging reduces sensitivity to noisy samples common in physiological signals.
3) **Regularization:** Built-in regularization prevents overfitting to limited training data.

The poor performance of AdaBoost, particularly for Subject 2 (52.4%), suggests sensitivity to outliers or class imbalance in certain datasets. KNN's moderate performance indicates that local neighborhood assumptions may not optimally capture fNIRS signal characteristics.

B. Inter-Subject Variability

Substantial accuracy variation across subjects (e.g., Subject 4: max 75.7% vs. Subject 2: max 91.4%) highlights the challenge of developing subject-independent classification models. Factors contributing to variability include:

- Anatomical differences affecting optode placement
- Physiological variations in hemodynamic response
- Cognitive strategy differences during task performance
- Signal quality variations due to hair, skin tone, or motion

Subject-specific model calibration or transfer learning approaches may be necessary for practical BCI applications.

C. GAN-Based Data Augmentation

The successful convergence of GAN training demonstrates feasibility for synthetic fNIRS data generation. Potential applications include:

- Augmenting limited training datasets for rare neurological conditions
- Generating balanced class distributions for imbalanced datasets
- Creating synthetic data for privacy-preserving model development

However, careful validation is required to ensure generated samples preserve physiologically meaningful characteristics rather than introducing artifacts.

D. Limitations

Several limitations should be acknowledged:

1) **Sample Size:** Eight subjects may not capture full population variability.
2) **Feature Set:** Additional features (frequency-domain, connectivity measures) may improve performance.
3) **GAN Validation:** Generated sample quality was assessed only through loss convergence; downstream task performance evaluation is needed.
4) **Real-time Processing:** Computational requirements for deployment were not evaluated.

VII. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive evaluation of machine learning algorithms and Generative Adversarial Networks for fNIRS brain signal classification. Key findings include:

1) XGBoost achieved the highest classification accuracy (91.43%) among evaluated algorithms, with LGBM

demonstrating consistent high performance across subjects.
2) Slope-related statistical features exhibited superior discriminative power for fNIRS signal classification.
3) Significant inter-subject variability necessitates subject-specific calibration for optimal performance.
4) GANs successfully learned fNIRS signal distributions, achieving training equilibrium with balanced generator-discriminator losses.

Future research directions include:

- **Deep Learning Architectures:** Implementing CNNs and LSTMs for end-to-end feature learning from raw fNIRS signals.
- **Transfer Learning:** Developing subject-adaptation techniques to reduce calibration requirements.
- **Multi-Modal Fusion:** Combining fNIRS with EEG for improved spatial-temporal resolution.
- **Real-Time Implementation:** Optimizing algorithms for embedded deployment in practical BCI systems.
- **Clinical Validation:** Evaluating model performance for neurological disorder diagnosis and monitoring.

The findings demonstrate that machine learning, particularly gradient boosting methods, offers effective tools for fNIRS-based brain-computer interfaces, while GANs provide promising capabilities for addressing data scarcity challenges in neuroimaging research.

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