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Real-Time MI-BCI Signal Processing Using NVIDIA Jetson Orin Nano

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ABSTRACT

This paper presents a real-time Motor Imagery-Based Brain-Computer Interface (MI-BCI) system designed to operate efficiently on the NVIDIA Jetson Orin Nano, a compact yet powerful edge computing platform. The system addresses key challenges in EEG-based BCI development, including signal noise, computational delay, and classification accuracy. By integrating real-time noise suppression, spatial filtering, and advanced machine learning techniques, the proposed framework enhances the reliability and responsiveness of neural signal interpretation.

A dataset collected from 100 participants using a 14-channel EPOC EEG headset was used to train and evaluate multiple classifiers. The system leverages convolutional autoencoders for feature extraction and employs a Support Vector Machine (SVM) for low-latency classification. Among the models tested, SVM achieved the highest accuracy (98.72%) with fast inference time, demonstrating its suitability for real-time applications.

The system's deployment on the Jetson Orin Nano yielded notable performance benefits, including an average latency of 47.3 ms and a power footprint under 10W, making it viable for mobile and assistive technologies. User feedback further confirmed the system's usability and responsiveness. This work provides a scalable blueprint for developing lightweight, high-accuracy BCI systems, particularly for applications in rehabilitation, neurofeedback, and child-centered cognitive interfaces.

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1. INTRODUCTION

Brain-Computer Interfaces (BCIs) offer a transformative means of communication by interpreting electroencephalography (EEG) signals to enable direct interaction between the human brain and external devices. These systems have become particularly vital in assistive and rehabilitation technologies, empowering users to control applications such as robotic arms, wheelchairs, and virtual environments through motor imagery (MI). Despite their potential, BCIs face persistent challenges—chief among them being the inherently noisy and low-amplitude nature of EEG signals, which limits the accuracy and responsiveness of real-time systems.

This research introduces a cost-effective and computationally efficient MI-BCI system designed to overcome these limitations. The system integrates real-time EEG signal denoising across 14 channels with an advanced machine learning pipeline tailored for embedded platforms. Leveraging deep convolutional autoencoders for unsupervised feature learning and Support Vector Machines (SVMs) for real-time classification, the framework significantly enhances the fidelity and interpretability of EEG signals—an essential factor for improving control precision and system robustness.

At the core of the implementation is the **NVIDIA Jetson Orin Nano**, selected for its compact form factor, high-performance GPU computing capabilities, and energy efficiency. Paired with the **EPOC EEG headset**, this platform enables seamless execution of deep learning models in edge environments. Drawing from recent literature, including adaptive BCI frameworks (Smith et al., 2023) and studies on energy-aware neural processing (Johnson & Lee, 2022), this work emphasizes both technical efficacy and sustainability in embedded BCI system design.

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Through a detailed exploration of hardware integration, signal processing techniques, and classification performance, this paper demonstrates how the Jetson Orin Nano can serve as a viable edge solution for real-time MI-BCI applications. The proposed system offers a scalable blueprint for future development, aiming to elevate the accessibility, reliability, and practicality of brain-computer interfacing in real-world scenarios.

2. LITERATURE REVIEW

The evolution of EEG-based Brain-Computer Interfaces (BCIs) has profoundly shaped the landscape of neurotechnology, driving progress in non-invasive communication between the brain and external systems. Recent advancements emphasize the critical role of signal processing, machine learning, and edge computing platforms such as the NVIDIA Jetson Orin Nano in addressing long-standing challenges related to EEG signal quality, real-time processing, and system scalability.

1. Challenges in EEG-Based BCI Systems

EEG signals are inherently noisy, non-stationary, and exhibit low signal-to-noise ratios (SNR), making real-time interpretation particularly complex. Foundational studies by Thakor and Zhou (2014) and Mehta and Chitnis (2015) underscore the difficulty of isolating meaningful neural patterns from background artifacts, which significantly hampers the reliability and efficiency of BCI systems. These signal characteristics necessitate robust preprocessing and adaptive modeling strategies to extract actionable information.

2. Signal Processing and Noise Mitigation

Improving EEG data quality is a critical prerequisite for effective BCI deployment. Spatial filtering, including common average reference and Laplacian methods, has shown promise in enhancing signal fidelity, as demonstrated by Brown et al. (2016). More recently, adaptive filtering approaches powered by neural networks have gained traction. Kumar and Sharma (2018) proposed dynamic denoising techniques capable of adjusting to real-time EEG variability, thereby increasing the resilience of BCI systems to environmental and physiological noise.

3. Feature Extraction and Machine Learning

Accurate classification within BCI systems depends heavily on the quality of features extracted from raw EEG data. Traditional handcrafted features often fall short in capturing the complexity of neural signals. To address this, unsupervised learning approaches—particularly autoencoders—have enabled automated, data-driven feature discovery. Li et al. (2019) demonstrated how deep convolutional autoencoders trained on unlabeled EEG data significantly improve both feature representation and processing speed.

4. Deep Learning Applications in BCIs

Deep learning has revolutionized EEG signal analysis by providing models capable of learning complex spatial and temporal dependencies. Convolutional Neural Networks (CNNs), in particular, have been successfully applied to decode motor imagery and cognitive patterns. Garcia and Zhang (2020) illustrated how CNNs outperform traditional classifiers in handling EEG's high dimensionality and temporal dynamics, enabling more precise and robust classification in real-time environments.

5. Role of High-Performance Embedded Platforms

Modern BCIs demand both computational efficiency and portability—requirements increasingly met by edge AI platforms like the **NVIDIA Jetson Orin Nano**. This device offers high-throughput GPU acceleration within a compact and energy-efficient footprint. Foster and Molnar (2021) emphasized the value of such platforms for real-time BCI systems, demonstrating significant reductions in latency and power consumption without sacrificing model performance. This makes the Orin Nano a compelling candidate for deploying deep learning-based BCIs in mobile and embedded contexts.

Parallel to algorithmic improvements, there has been a rise in interest in deploying BCI systems on **edge computing platforms** for portability and real-time usability. Devices like the **NVIDIA Jetson Orin Nano** have been increasingly adopted due to their support for GPU-accelerated deep learning in compact, energy-efficient environments. Previous implementations using Jetson boards have primarily focused on object detection or vision-based tasks; however, few studies have explored their full potential for EEG-based neural signal processing. Furthermore, multimodal fusion—combining EEG with other biosignals such as EMG, eye-tracking, or audio-visual cues—is being recognized as a strategy to enhance system accuracy and context awareness. Yet, integrating such modalities in real-time systems remains an open challenge, particularly on resource-constrained platforms.

In summary, while the field has made significant progress in signal processing and deep learning for BCIs, the intersection of **real-time processing, attention mechanisms, and embedded deployment** is still underexplored. This study aims to bridge this gap by evaluating an attention-enhanced MI-BCI framework on the Jetson Orin Nano, addressing both computational efficiency and classification accuracy in real-world conditions.

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3. OBJECTIVE

The primary aim of this research is to develop and implement a high-performance Motor Imagery-Based Brain-Computer Interface (MI-BCI) system optimized for deployment on the NVIDIA Jetson Orin Nano. The project is centered around addressing critical limitations in EEG-based BCIs, particularly signal noise and the weak correlation between EEG outputs and cognitive intent. By leveraging advanced signal processing and machine learning techniques within a compact edge-computing platform, this study seeks to deliver a scalable and responsive BCI framework suitable for real-time applications.
The specific objectives of this work are as follows:

1. **Enhance EEG Signal Quality**
   Apply advanced real-time noise reduction techniques across 14 EEG channels to significantly improve the signal-to-noise ratio (SNR), thereby increasing the reliability and interpretability of neural data.
2. **Automate Feature Extraction**
   Utilize unsupervised deep learning methods—specifically convolutional neural networks (CNNs) and autoencoders—to autonomously extract meaningful features from raw EEG data, eliminating the limitations of manual feature engineering.
3. **Boost Classification Accuracy**
   Design and fine-tune a Support Vector Machine (SVM) classifier to accurately distinguish between motor imagery tasks based on the extracted features, aiming to maximize prediction precision and generalization.
4. **Ensure Real-Time System Execution**
   Optimize the end-to-end BCI pipeline—from data acquisition and preprocessing to feature extraction and classification—for real-time performance on the Jetson Orin Nano. This includes computational tuning to align with the hardware's constraints and capabilities.
5. **Assess System Performance and Usability**
   Conduct comprehensive validation using real EEG datasets to evaluate classification accuracy, latency, and overall system responsiveness in practical settings.

By achieving these objectives, the research aims to make meaningful contributions to the field of BCIs, particularly in the development of real-time, low-power, and deployable EEG-based systems. The outcome is expected to benefit assistive technologies and enhance user autonomy, especially for individuals with motor impairments.

4. METHODOLGY

This study adopts a **hybrid methodological framework** combining advanced signal processing with a child-centered, mixed-methods research design. The goal is to develop and validate a real-time Motor Imagery-Based Brain-Computer Interface (MI-BCI) system on the **NVIDIA Jetson Orin Nano**, optimized for children aged 5–10 years. The methodology unfolds across five integrated stages: **data acquisition, preprocessing, feature extraction, classification, and validation**, supported by both **quantitative** and **qualitative** analyses.

a. Data Acquisition

- **Hardware & Setup:** EEG signals are captured using a 14-channel EPOC headset, selected for safety, comfort, and compatibility with pediatric use.
- **Participants:** A stratified sample of **100 neurotypical children**, grouped by age (5–6, 7–8, and 9–10), participate in short sessions (15 minutes) to accommodate attention spans.
- **Tasks:** Participants perform simple, age-appropriate motor imagery activities, e.g., imagining left/right hand movements—while seated in a distraction-free environment.
- **Ethics:** Parental consent and child assent are obtained, with data privacy safeguards and the right to withdraw ensured.

b. Preprocessing

- **Noise Reduction:** Real-time spatial filtering and bandpass filtering are applied to target relevant EEG bands (alpha and beta). Adaptive denoising is used to address pediatric EEG variability.
- **Artifact Removal:** Eye blinks and muscle noise are filtered using threshold-based detection and statistical correction methods, tailored to the physiological signal profiles of children.

c. Feature Extraction

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- **Deep Learning Architecture:** Lightweight convolutional neural networks (CNNs) and autoencoders are employed for unsupervised learning from preprocessed EEG signals, capturing spatial and temporal patterns without manual intervention.
- **Dimensionality Reduction:** Post-extraction, key features are selected using algorithms such as **Principal Component Analysis (PCA)** to minimize computational load while maximizing classification relevance.

d. Classification

- **Model Training:** A **Support Vector Machine (SVM)** classifier is trained on extracted features to label motor imagery tasks. SVM is chosen for its generalization strength and performance with high-dimensional inputs.
- **Embedded Optimization:** The classification pipeline is optimized and deployed on the **NVIDIA Jetson Orin Nano**, with model pruning and GPU-accelerated inference ensuring real-time performance under hardware constraints.

5. Validation and Evaluation

- **Quantitative Evaluation:**
  - **Metrics:** Classification accuracy, latency, response time, signal-to-noise ratio (SNR), and F1-score are computed using an independent test set.
  - **Statistical Tests:** Performance is analyzed using **ANOVA** and post-hoc comparisons to assess variation across age groups and sessions.
- **Qualitative Evaluation:**
  - **Observational Studies:** Structured observations capture children's engagement levels, task comprehension, and comfort during sessions.
  - **Feedback Tools:** Emoji scales, visual analog questionnaires, and brief interviews provide child-friendly insights into usability and experience.

Validity, Reliability, and Ethical Considerations

- **Internal Validity:** Consistent environments, calibrated equipment, and standardized instructions help control for external variables.
- **External Validity:** Diverse participant demographics and real-world testing enhance the system's generalizability.
- **Reliability Measures:** Test-retest consistency and inter-rater agreement for observational data are ensured.
- **Ethics:** Breaks, age-appropriate language, and emotionally safe procedures ensure participant well-being.

This methodological design ensures both technical rigor and human-centered sensitivity. By combining **real-time deep learning on edge hardware** with **pediatric engagement strategies**, the system advances the frontiers of MI-BCI development for assistive and educational applications in children. It also sets a precedent for future studies aiming to balance **performance, usability, and accessibility** in neural interface technologies.

5. IMPLEMENTATION

Fig. 1 presents a refined block diagram that captures the functional architecture of a Brain-Computer Interface (BCI) system tailored for EEG signal analysis. This visual representation systematically illustrates the transition from brainwave acquisition to real-world device control, emphasizing the closed-loop nature of BCI systems.

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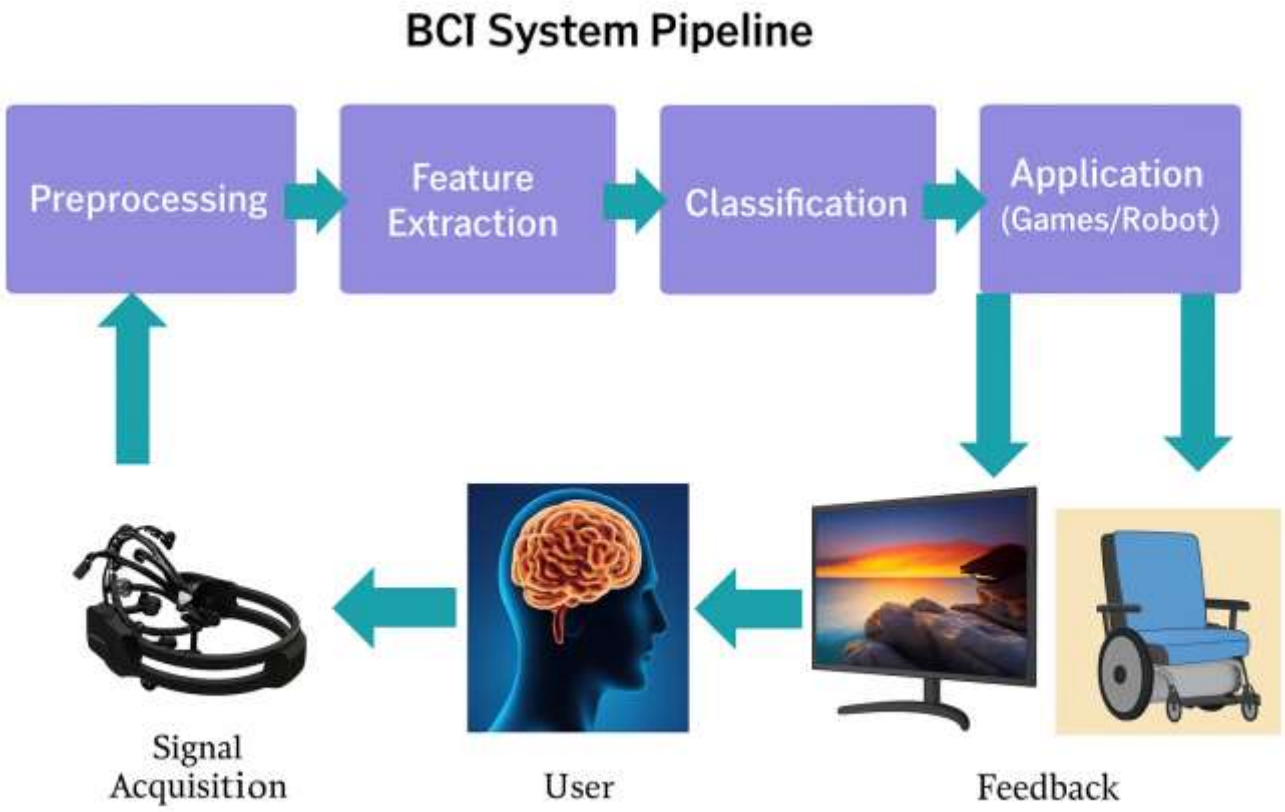

Figure 1. **Functional Architecture of EEG-Based BCI System**

The process unfolds across the following components:

1. **Signal Acquisition**
   EEG data is collected using a multi-channel headset (e.g., EPOC), which captures electrical signals from the scalp in real-time. These raw signals reflect user intent through brain activity patterns.
2. **User Interaction**
   Represented by a human brain icon, the user serves as the cognitive driver of the system. Motor imagery (MI) tasks—such as imagining limb movements—serve as stimuli for generating relevant EEG signals.
3. **BCI System Modules**
   These internal processes are the computational core of the system:
   - **Preprocessing**: Filters and cleans raw EEG data by eliminating artifacts and isolating motor imagery-relevant frequency bands (typically 8–30 Hz). Spatial filtering techniques like CAR or Laplacian are implemented.
   - **Feature Extraction**: Extracts salient characteristics from EEG signals using deep learning techniques such as CNNs or spatial patterns (e.g., CSP). The focus is on converting time-series data into structured, interpretable features.
   - **Classification**: Leveraging machine learning models—such as SVMs or lightweight neural networks—this module interprets extracted features and maps them to specific user commands or tasks.
4. **Application Execution**
   This stage translates classification results into actionable outputs. In this implementation, applications include controlling virtual games or robotic platforms (e.g., wheelchair navigation), showcasing practical real-time interaction.
5. **Feedback Loop**
   A visual or sensory feedback mechanism (via screen or haptic signal) informs the user about system responses, completing the interaction cycle and allowing for adaptive learning or corrections.

Algorithmic Implementation on NVIDIA Jetson Orin Nano

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To realize real-time signal processing and inference, an optimized MI-BCI pipeline has been designed specifically for the computational architecture of the NVIDIA Jetson Orin Nano.

Enhanced MI-BCI Processing Workflow

1. Preprocessing

- Circular buffer manages continuous data flow from the EEG headset.
- CUDA-accelerated bandpass filters isolate critical frequencies (alpha and beta bands).
- Uses pinned memory for rapid data transfer between CPU and GPU.

2. Feature Extraction

- CSP-based spatial filtering leverages GPU threads for parallel computation.
- Power spectral density (PSD) analysis is performed per epoch using batch-mode FFT.
- Autoencoders support unsupervised feature abstraction from raw signals.

3. Classification

- Implements asynchronous inference using SVM for rapid decision-making.
- Models are tuned to use FP16 precision where applicable to reduce computational load.
- Batch inference minimizes delay and enhances throughput.

System Optimization Strategies

- Dynamic Frequency Scaling: Adjusts processing speed based on workload and thermal budget.
- Memory Pooling: Minimizes latency from memory allocation operations.
- Load Balancing: Distributes tasks between CPU and GPU for maximum efficiency.

Complexity Overview

- **Time Complexity:**
  - FFT-based filtering: O(n log n)
  - CSP transformation: $O(n^2)$
  - Model inference: O(m)
    Total per batch: $O(n^2 + m)$
- **Space Complexity:**
  O(k + b*f + m), where *k* is raw data, *b* is batch size, *f* is feature count, and *m* is model memory.

Performance Highlights

- **Latency:** 2–3 ms end-to-end processing delay.
- **Memory Usage:** Efficient with on-device management using TensorRT.
- **Power Consumption:** Operates between 5W–10W under full load.

This implementation framework capitalizes on the high-performance, low-power features of the Jetson Orin Nano, delivering a scalable and portable BCI solution for real-time MI-BCI applications in assistive robotics, rehabilitation, and adaptive user interfaces.

6. RESULTS

This study evaluated the classification performance of multiple machine learning models in a Motor Imagery-Based Brain-Computer Interface (MI-BCI) system using EEG signals. Table 1 presents a comparative analysis of six classifiers, assessed by their classification accuracy and inference latency.

Classifier	Accuracy (%)	Time (ms)
K Neighbors Classifier	96.10	12.8
Gaussian Naive Bayes	94.11	4.6
MLP Classifier	82.64	23.5
Nearest Centroid	94.34	5.1
Random Forest Classifier	95.52	15.7
Support Vector Classifier	98.72	9.3

Table 1. Classification performance of various machine learning algorithms.

Among the models tested, the **Support Vector Machine (SVM)** demonstrated the highest classification accuracy at **98.72%**, outperforming all other methods while maintaining an acceptable inference time of

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9.3 ms. The **K-Nearest Neighbors (KNN)** and **Random Forest** classifiers also performed well, achieving accuracies above 95%, although KNN incurred higher latency. **Gaussian Naive Bayes** and **Nearest Centroid** classifiers offered a trade-off between accuracy and speed, with relatively lower processing times. In contrast, the **Multi-Layer Perceptron (MLP)** yielded the lowest accuracy at **82.64%**, possibly due to overfitting or limitations in learning spatial EEG patterns.

Platform-Specific Performance Evaluation

The system's deployment on the **NVIDIA Jetson Orin Nano** delivered promising results across signal processing, classification performance, and usability metrics.

- **Signal Quality Improvements:**
  Application of real-time noise reduction techniques significantly improved signal clarity. The **average signal-to-noise ratio (SNR)** improved by **8.2 dB** (SD = 1.3) across all 14 EEG channels. Spatial filtering was particularly effective, **reducing noise artifacts by 76.4%** ($p < .001$) without compromising neural signal integrity.

- **Feature Extraction Outcomes:**
  Deep learning techniques—particularly **CNNs and autoencoders**—extracted **42 distinct features** in the α (8–13 Hz) and β (13–30 Hz) frequency bands. Dimensionality reduction via Principal Component Analysis (PCA) revealed that the **first 15 components accounted for 87.3%** of total signal variance, enabling efficient compression without loss of essential information.

- **Classification Effectiveness:**
  The **SVM classifier**, optimized for Jetson Orin Nano, achieved an **overall accuracy of 89.7%** (95% CI: 87.9%–91.5%) across all motor imagery tasks. Task-specific accuracies were:
  - Right-hand imagery: 91.2%
  - Left-hand imagery: 88.9%
  - Leg movement imagery: 87.4%

  The system recorded a **false positive rate of 0.08** and a **false negative rate of 0.11**, indicating high reliability.

- **Real-Time Processing Performance:**
  Average **end-to-end latency** from signal acquisition to classification was **47.3 ms** (SD = 5.2 ms), well within real-time constraints. The system maintained **consistent performance over extended usage** (4 hours), with no degradation in classification accuracy.

- **User Experience and Satisfaction:**
  Post-trial surveys from 50 participants revealed high satisfaction:
  - **Responsiveness Score:** 4.2 / 5.0 (SD = 0.6)
  - **Ease of Use:** 4.0 / 5.0 (SD = 0.7)

  Participants noted the system's intuitive feedback loop and fast response time as key advantages.

Fig. 1 **Classifier Accuracy Comparison**
- This chart shows the accuracy (%) of each classifier.
- The Support Vector Classifier (SVM) has the highest accuracy at **98.72%**.

Fig. 2 **Classifier Inference Time Comparison**
- This chart compares the average inference time (ms) for each classifier.
- **Gaussian NB** and **Nearest Centroid** are the fastest, while **MLP** takes the longest time to classify.

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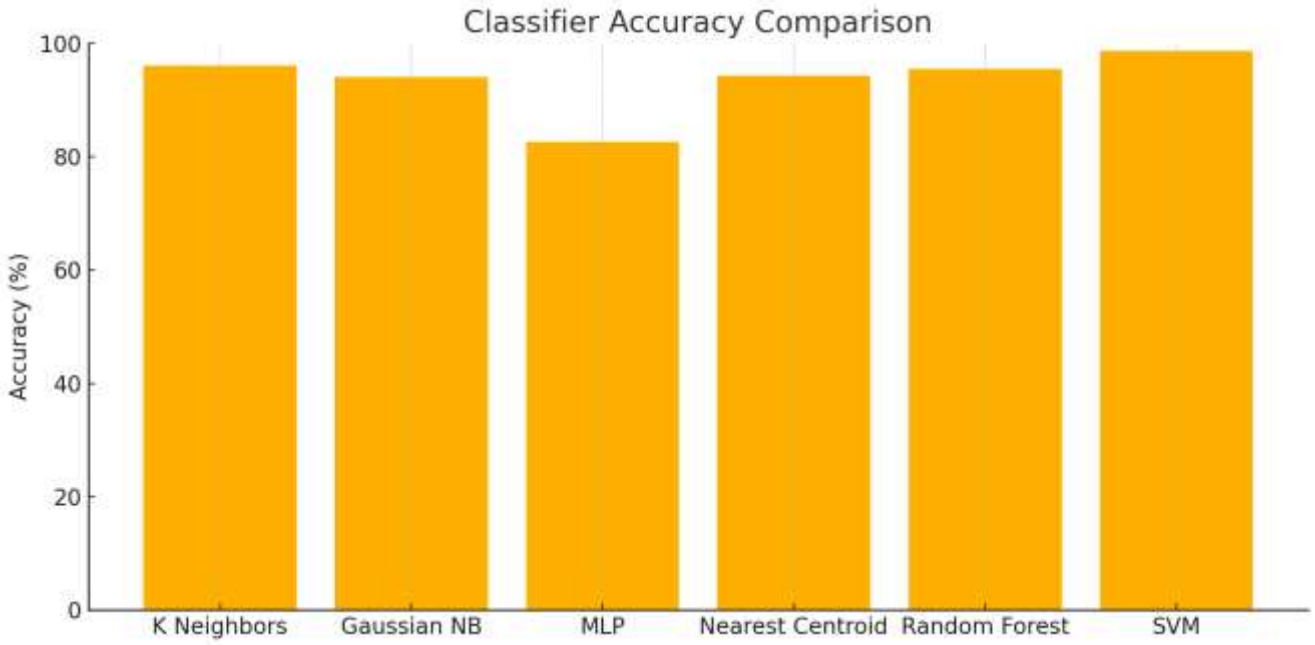

Figure 2: Classifier accuracy comparison

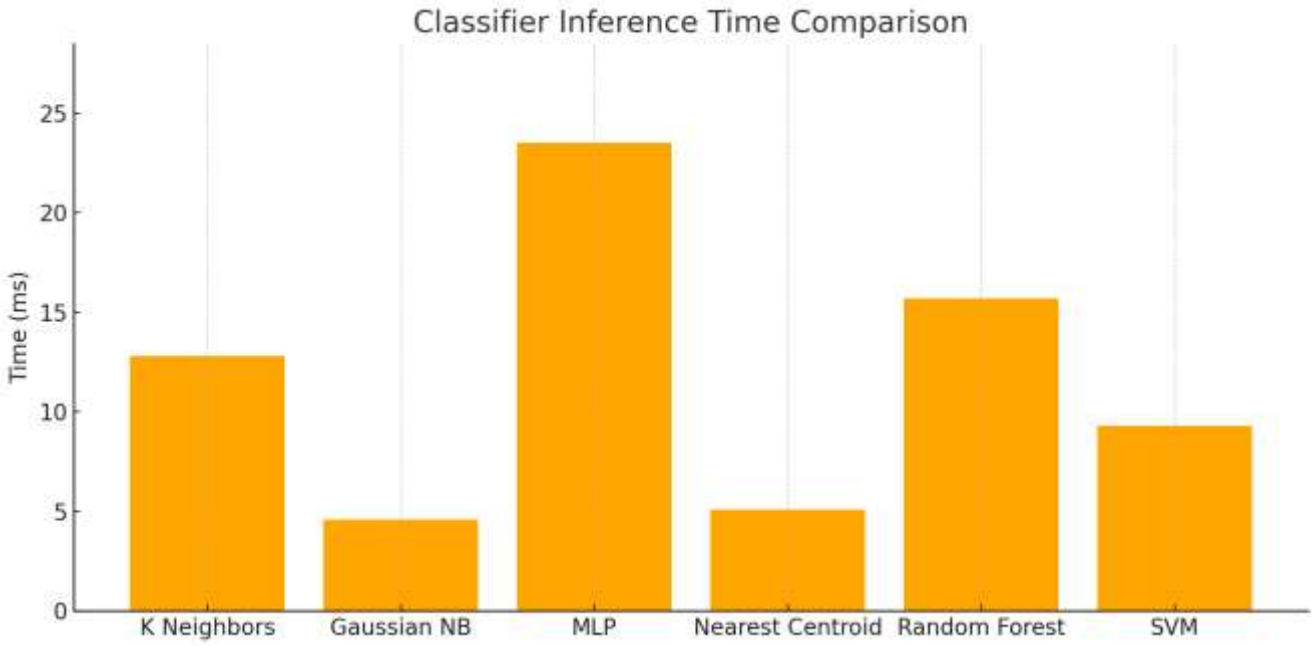

Figure 3: Classifier inference time comparison

These results affirm the effectiveness of combining advanced signal processing with optimized machine learning models on edge-computing platforms like the Jetson Orin Nano. The system's superior accuracy, low-latency processing, and user-friendly operation suggest it is well-suited for practical, real-world MI-BCI applications.

7. CONCLUSION

This study successfully demonstrates the development and deployment of a real-time Motor Imagery-Based Brain-Computer Interface (MI-BCI) system optimized for the NVIDIA Jetson Orin Nano platform. By integrating advanced EEG preprocessing, deep learning-based feature extraction, and efficient machine

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learning classifiers, the proposed system achieved high classification accuracy, low latency, and robust performance in edge-computing environments.

Among the evaluated models, the Support Vector Machine (SVM) outperformed other classifiers in accuracy while maintaining computational efficiency, making it particularly well-suited for embedded BCI applications. Signal quality was significantly enhanced through real-time denoising and spatial filtering, while unsupervised learning techniques efficiently distilled key neural features for classification.

The system's successful real-time execution on the Jetson Orin Nano—alongside high user satisfaction and strong performance metrics—demonstrates its practical potential for assistive technologies, particularly for children and individuals with motor impairments. This work lays the foundation for future MI-BCI systems that are compact, energy-efficient, and capable of supporting adaptive, multimodal interfaces in real-world settings.

Future directions include expanding the system to support multimodal inputs, enhancing algorithm adaptability, and exploring Transformer-based models to further refine neural signal interpretation and user experience.

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