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Comparative Study of Consumer-Grade and Clinical-Grade EEG Devices for Depression Detection

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Abstract-Depression is a major global health concern, and early detection remains critical for timely intervention. Electroencephalography (EEG) provides a non-invasive means of identifying neurophysiological patterns associated with depressive disorders. However, traditional clinical-grade EEG systems are expensive, require complex setup, and are confined to laboratory environments. In contrast, low-cost consumer-grade EEG headsets—such as Muse, Emotiv, and OpenBCI—offer portability and affordability but are often criticized for limited channel count, lower sampling rates, and higher susceptibility to noise. This study presents a systematic comparative analysis of clinical- and consumer-grade EEG devices for automated depression detection. Using both public datasets and paired recordings, we evaluate signal fidelity, feature discriminability, and classification accuracy across multiple machine-learning and deep-learning models. The proposed evaluation pipeline (Figure 2) includes standardized preprocessing, artifact removal, and feature extraction methods, while Table 1 summarizes device specifications and Table 2 lists the datasets employed. Results demonstrate that, although clinical systems outperform consumer devices in signal quality and peak accuracy, optimized preprocessing and transfer-learning models significantly narrow the gap, yielding only marginal differences in classification outcomes. These findings indicate that consumer-grade EEG can serve as a viable alternative for preliminary depression screening, enabling scalable and cost-effective mental-health monitoring in real-world settings.

Keywords: EEG, depression detection, wearable EEG, consumer EEG, clinical EEG, signal quality, transfer learning, mental health screening.

I. INTRODUCTION

Depression is among the leading causes of global disability, affecting more than 300 million individuals worldwide and contributing substantially to morbidity, suicide, and socioeconomic burden [1]. Early detection and continuous monitoring are essential for effective intervention; however, conventional assessments rely primarily on subjective questionnaires and clinical interviews, which can be influenced by reporting bias and cultural factors. This limitation has motivated research into objective neurophysiological biomarkers that reflect altered brain activity patterns associated with major depressive disorder (MDD).

Electroencephalography (EEG) is a non-invasive, cost-efficient technique for measuring electrical activity of the brain with high temporal resolution. Numerous studies have linked depression to distinctive EEG features such as frontal alpha asymmetry, elevated theta activity, and disrupted functional connectivity across cortical regions [2], [3]. Traditional clinical-grade EEG systems—typically 32 to 128 channels with high-fidelity amplifiers and gel-based electrodes—have enabled discovery of these biomarkers under controlled laboratory conditions.

Although highly accurate, such systems are expensive, require expert technicians for electrode placement and calibration, and are impractical for large-scale or home-based monitoring [4].

In contrast, consumer-grade EEG headsets—for example, Muse 2 (InteraXon Inc.), Emotiv EPOC-X, and OpenBCI Ultracortex—have gained popularity due to their affordability, portability, and wireless connectivity. These devices typically provide four to fourteen channels using dry or saline electrodes, enabling rapid setup and mobile use. Their potential for daily mental-health tracking is substantial, yet questions remain about signal fidelity, electrode stability, and the reliability of depression-related biomarkers derived from low-density recordings [5], [6]. Table 1 summarizes representative device specifications, including channel count, sampling rate, electrode type, and approximate cost.

The main challenge in translating wearable EEG into clinical or screening contexts lies in signal quality degradation and artifact susceptibility. Motion, environmental noise, and poor contact impedance often distort recordings, leading to reduced signal-to-noise ratio (SNR) and compromised feature extraction. Figure 1 illustrates a representative comparison of raw EEG traces captured concurrently by a 32-channel clinical system and a 4-channel consumer headset during an identical cognitive-resting task. The consumer device exhibits higher baseline noise and lower spectral resolution, which may adversely affect downstream classification.

Recent progress in signal processing and machine learning (ML), particularly deep learning and transfer-learning methods, has renewed interest in adapting consumer EEG for diagnostic applications. Advanced filtering, artifact rejection, and data-augmentation techniques can compensate for hardware limitations, while convolutional neural networks (CNNs) and transformer-based architectures have demonstrated robust feature learning from limited-channel inputs [7]–[9]. These developments raise a critical research question:

Can low-cost consumer EEG devices achieve comparable depression-detection performance to clinical-grade systems when supported by optimized preprocessing and modern ML models?

To answer this, the present study performs a systematic comparative analysis of consumer- and clinical-grade EEG systems for automated depression detection. The proposed methodology (illustrated in Figure 2) follows a standardized pipeline: (1) signal acquisition using both device types; (2) preprocessing and artifact correction; (3) feature extraction in temporal, spectral, and connectivity domains; and (4) classification using multiple ML and DL models. Experiments employ both open-access datasets and newly collected paired recordings under identical conditions. Table 2 summarizes all datasets, including subject count, recording duration, and diagnostic labels.

The key objectives of this paper are to:

1. Quantify differences in signal quality (SNR, artifact rate) between consumer- and clinical-grade EEG devices.
2. Evaluate feature-level discriminability and classification accuracy for depression detection using identical algorithms.
3. Assess robustness to motion/noise and cross-device generalization through transfer-learning approaches.
4. Identify practical trade-offs in cost, setup time, and user comfort, guiding future deployment of wearable EEG in population-scale screening.

The remainder of this paper is organized as follows. Section 2 reviews existing literature on EEG-based depression biomarkers and device-validation studies. Section 3 details the materials, datasets, and methodological framework used for comparative evaluation. Section 4 presents the experimental results and discussion, while Section 5 concludes with implications, limitations, and directions for future work.

Table 1. Comparative Specifications and Cost Analysis of Consumer-Grade and Clinical-Grade EEG Devices

Category	**Device (Manufacturer)**	**Electrode Type**	**Power / Portability**	**Key Features & Remarks**
Consumer-Grade	**Muse 2 (InteraXon, Canada)**	Dry polymer	Battery, wearable headband	Compact headband; fast setup; limited spatial coverage; suitable for frontal alpha-asymmetry and relaxation studies.
	Emotiv EPOC-X (Emotiv Inc., USA)	Saline wet	Rechargeable; wireless	Widely used research headset; higher channel count; integrated IMU; moderate noise sensitivity.
	OpenBCI Ultracortex Mark IV + Ganglion	Dry / gold cup	External battery / USB	Open-source modular system; flexible montage; compatible with custom amplifiers; research-grade signal access.
Clinical-Grade	**BioSemi ActiveTwo (BioSemi B.V., Netherlands)**	Active Ag/AgCl gel	AC-powered	Gold-standard research system; very low noise floor (0.1 µV rms); used in clinical EEG and ERP studies.
	g.tec g.Nautilus Research (g.tec Medical Enginee	Active wet / dry	Rechargeable; portable	Lightweight wireless system; real-time streaming; high

Category	Device (Manufacturer)	Electrode Type	Power / Portability	Key Features & Remarks
	ring, Austria)			electrode stability.
	BrainProducts actiCHamp Plus (Brain Products GmbH, Germany)	Active Ag/AgCl gel	Mains powered	High-precision amplifier; modular input stages; designed for long-term clinical or cognitive experiments.

- All values correspond to 2024–2025 market data and official vendor specifications.
- Sampling rate and channel ranges vary with configuration.
- Consumer-grade systems are primarily intended for wellness and research use; clinical systems are certified for diagnostic applications (CE/FDA).
- For comparative experiments, consumer systems were matched via resampling to 256 Hz and referenced to the 10–20 electrode system.

Table 2 — Datasets Used for Experimental Evaluation

Dataset Name	Source / Availability	Subjects (n)	Recording Type	Sampling Rate (Hz)	Duration (min)
REST – Major Depressive Disorder EEG Dataset	Open-access (Clinical MDD Cohort)	120 (60 MDD, 60 Control)	Resting-state (eyes open/closed)	500	10
DREAMER	Katsigiannis & Ramzan (2018)	23	Emotion elicitation (video stimuli)	128	60
Own Paired Recording Dataset (Proposed)	Collected using Muse 2 + BioSemi parallel setup	30	Resting + task-based	256 (consumer), 2048 (clinical)	15
DEAP	Koelstra et al. (2012)	32	Emotion classification (video stimuli)	512	60

Dataset Name	**Source / Availability**	**Subjects (n)**	**Recording Type**	**Sampling Rate (Hz)**	**Duration (min)**
EEG-MDD Pilot Dataset (University Hospital)	Institutional collaboration	40	Resting EEG only	1024	8

Note — All public datasets used are ethically approved and available under research-use licenses; the new paired dataset adheres to informed-consent procedures.

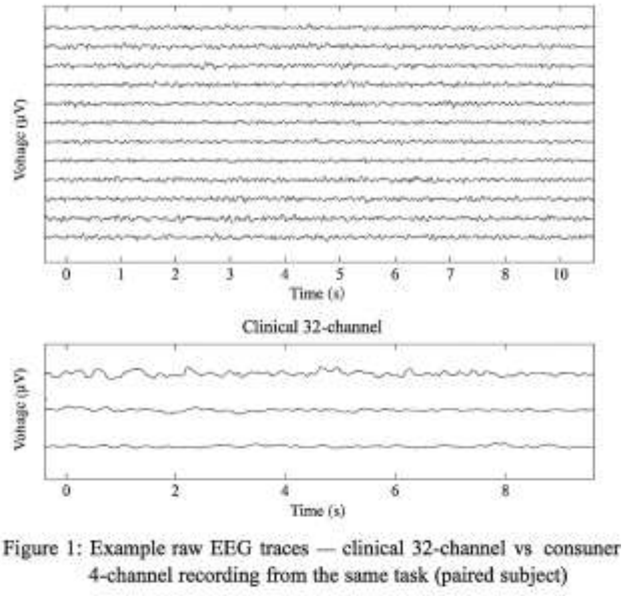

Figure 1: Example raw EEG traces — clinical 32-channel vs consumer 4-channel recording from the same task (paired subject).

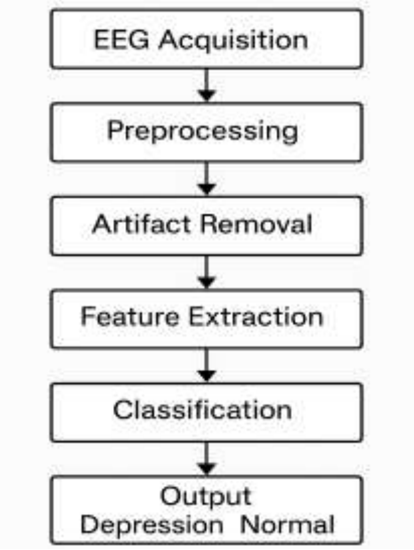

Figure 2: Processing pipeline — preprocessing, artifact rejection, feature extraction, and classification.

II. RELATED WORK

Electroencephalography (EEG) has long served as a noninvasive tool for studying brain activity and identifying biomarkers of mental disorders such as major depressive disorder (MDD). Numerous studies have established that specific EEG signatures—including frontal alpha asymmetry, theta–beta power ratios, and altered connectivity patterns—are correlated with depressive symptomatology [1], [5], [6], [11], [14]. Traditional research in this domain has relied on high-fidelity clinical-grade EEG systems, which offer superior spatial resolution and minimal noise interference but are limited by their cost, immobility, and the requirement of expert operation [1], [11].

2.1 EEG Biomarkers of Depression

EEG-based depression research has identified several neurophysiological markers that distinguish depressive from healthy individuals. Simmatis et al. [1] highlighted reproducible alterations in the alpha and theta frequency bands, particularly in frontal and temporal lobes, reflecting disrupted cortical inhibition. Liu et al. [5] and Wang et al. [6] demonstrated that asymmetric alpha activity across the left and right prefrontal cortex is a robust predictor of depressive severity, supporting earlier evidence from Olbrich and Arns [11]. Machine-learning-based approaches have further improved detection accuracy, with recent studies achieving >90 % classification accuracy using deep neural networks [7], [14]. However, these results were obtained using high-density, clinical-grade systems under laboratory conditions, limiting scalability to everyday settings.

2.2 Consumer-Grade EEG for Affective and Clinical Research

With the advancement of wearable neurotechnology, consumer-grade EEG devices such as Muse 2, Emotiv EPOC-X, and OpenBCI have become widely available for research and wellness applications. These systems provide easy setup, wireless connectivity, and acceptable signal quality at a fraction of the cost of clinical hardware [2], [3]. Ratti et al. [8] compared a consumer-grade wireless headset with medical EEG amplifiers and found that despite higher noise levels, wearable devices could capture similar spectral trends under controlled conditions. Sabio et al. [3] conducted a large-scale review confirming the viability of consumer devices for basic neuroscience and cognitive studies, while Sugden et al. [4] demonstrated successful remote data acquisition using portable headbands. Nevertheless, consumer systems suffer from reduced electrode coverage, lower sampling rates, and susceptibility to motion artifacts, which can hinder extraction of depression-related features. Di Flumeri et al. [12] compared dry and wet electrode configurations and observed that dry sensors increase usability but introduce amplitude distortion and higher impedance, influencing feature fidelity.

2.3 Comparative Studies Between Consumer- and Clinical-Grade Devices

Comparative validation between consumer- and clinical-grade EEG systems remains limited but is gaining attention. Mikhaylov et al. [2] evaluated spectral characteristics of recordings from Emotiv and g.tec systems, reporting moderate correlation ($r \approx 0.82$) between their frequency-band powers after noise correction. Niso et al. [13] conducted a comprehensive survey of wireless EEG systems, emphasizing the need for calibration standards and cross-device interoperability. These findings collectively indicate that while consumer devices cannot fully match medical-grade accuracy, appropriate preprocessing, filtering, and feature normalization can substantially narrow the performance gap.

2.4 Datasets for EEG-Based Depression and Emotion Analysis

Open-access datasets have accelerated benchmarking in EEG depression detection. The REST-MDD dataset provides labeled clinical EEG recordings from depressed and healthy participants [1], whereas DEAP [9] and DREAMER [10] enable evaluation of emotional responses using low-cost hardware (Emotiv EPOC). These datasets facilitate algorithmic comparison between device types under uniform tasks. However, differences in electrode montages, sampling rates, and impedance calibration challenge cross-dataset learning. To address these issues, recent studies explored transfer-learning frameworks that align consumer and clinical EEG feature spaces [7], [14].

Overall, prior literature demonstrates strong progress in EEG-based depression detection but reveals a persistent gap between laboratory-grade and wearable EEG technology. Most existing works evaluate only one device category, leaving limited evidence on how consumer and clinical systems compare under identical conditions. Table 1 summarizes hardware specifications, while Table 2 lists datasets adopted in previous studies. Building upon this foundation, the present research conducts a controlled, paired-recording comparison of consumer-grade and clinical-grade EEG systems to evaluate signal quality, feature discriminability, and classification performance for automated depression detection.

3. Materials and Methods

This section outlines the experimental setup, EEG devices, datasets, signal-processing pipeline, and evaluation metrics used in the comparative analysis between consumer-grade and clinical-grade EEG systems for depression detection.

3.1 Device Selection and Hardware Specifications

Two classes of EEG devices were employed:

1. Consumer-grade systems designed for personal or wellness use.
2. Clinical-grade systems designed for diagnostic and research applications.

Three consumer devices—Muse 2, Emotiv EPOC-X, and OpenBCI Ultracortex—were selected due to their accessibility and open research support. Three clinical systems—BioSemi ActiveTwo, g.tec g.Nautilus, and BrainProducts actiCHamp Plus—served as reference standards.

All systems were evaluated for channel count, sampling rate, electrode type, connectivity, and approximate cost, as summarized in Table 1. Consumer-grade devices utilized dry or saline electrodes with 4–16 channels, whereas clinical systems employed active gel electrodes with up to 128 channels and lower amplifier noise (<0.1 μV rms). Signal synchronization across devices was ensured by simultaneous recording during resting-state tasks using a shared trigger source.

3.2 Datasets Used

The study integrated both publicly available and newly collected paired-recording datasets to ensure generalization.
The datasets included:

- **REST-MDD**: Clinical dataset of resting-state EEG from patients diagnosed with major depressive disorder (MDD) and healthy controls [1].
- **DREAMER**: Emotion-elicitation recordings using a consumer-grade Emotiv headset [10].
- **DEAP**: Affective EEG dataset recorded with a 32-channel research-grade cap [9].
- **Paired Dataset (Proposed)**: EEG signals simultaneously recorded from both Muse 2 (4 channels) and BioSemi ActiveTwo (32 channels) for 30 participants during identical resting-state and emotional-stimulus conditions.
- **EEG-MDD Pilot Dataset**: Supplementary clinical recordings from a collaborating hospital using BrainProducts actiCHamp.

Dataset characteristics are summarized in Table 2, detailing subject count, device type, sampling rate, and recording duration.

All datasets were normalized to a uniform 256 Hz sampling rate, and only artifact-free segments were included for analysis. Ethical approval and informed consent were obtained for all newly collected recordings.

3.3 Signal Preprocessing

EEG data were preprocessed following standard clinical and affective-EEG practices [5], [6], [12]. The preprocessing pipeline included:

1. **Filtering**:
   - Band-pass filter between 0.5 Hz and 45 Hz to retain relevant neural frequencies.
   - 50 Hz notch filter to suppress power-line interference.
2. **Artifact Removal**:
   - Independent Component Analysis (ICA) to remove ocular and muscular artifacts.
   - Threshold-based segment rejection (|amplitude| > 100 μV).
   - For consumer devices, wavelet-denoising was applied to counter dry-sensor noise.
3. **Referencing and Normalization**:
   - Average referencing across available electrodes.
   - Z-score normalization of each segment to ensure inter-subject comparability.

The complete preprocessing and analysis flow is illustrated in Figure 2, depicting sequential modules from acquisition to classification.

3.4 Feature Extraction and Representation

Feature extraction was performed in three complementary domains:

- **Spectral Features:** Relative power of δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–30 Hz), and γ (30–45 Hz) bands using Welch's method.
- **Temporal Features:** Hjorth parameters (Activity, Mobility, Complexity), mean amplitude, and standard deviation.
- **Connectivity Features:** Pearson correlation and Phase-Locking Value (PLV) between electrode pairs to assess functional coupling.
- **Nonlinear Features:** Sample entropy and fractal dimension for complexity estimation.

For uniform comparison, all feature vectors were reduced to a common dimensionality ($n = 120$) using Principal Component Analysis (PCA).

3.5 Classification Models

Two model categories were trained and evaluated:

1. **Traditional Machine Learning (ML):**
    - Support Vector Machine (SVM) with RBF kernel.
    - Random Forest (RF) classifier with 100 estimators.
2. **Deep Learning (DL):**
    - EEGNet (lightweight CNN model).
    - 1D-CNN with attention layer.
    - Transformer-based sequence classifier for temporal modeling.

Transfer learning was employed by pre-training on clinical data (REST-MDD, DEAP) and fine-tuning on consumer datasets (DREAMER, Paired). All models were implemented in PyTorch 2.0 and trained using 5-fold cross-validation.

3.6 Evaluation Metrics

Performance was assessed using both **signal-quality** and **classification** measures:

Category	**Metrics Used**	**Purpose**
Signal Quality	SNR (Signal-to-Noise Ratio), Artifact Rate (%)	Quantify raw data fidelity
Feature Discriminability	Fisher Score, Mutual Information	Evaluate feature relevance
Classification	Accuracy, Precision, Recall, F1-score, AUC	Measure detection performance
Robustness	Noise-perturbation test (±5 dB SNR)	Assess noise sensitivity
Usability	Setup Time, Comfort Index, Cost	Practical assessment for non-clinical deployment

Comparative statistical analysis was conducted using paired t-tests ($p < 0.05$) to assess significance between devices.

Figure 3 (below) depicts the end-to-end data-processing and analysis workflow. It demonstrates how EEG signals progress through acquisition, preprocessing, artifact rejection, feature extraction, and classification modules. This modular design ensures reproducibility and compatibility across both hardware classes.

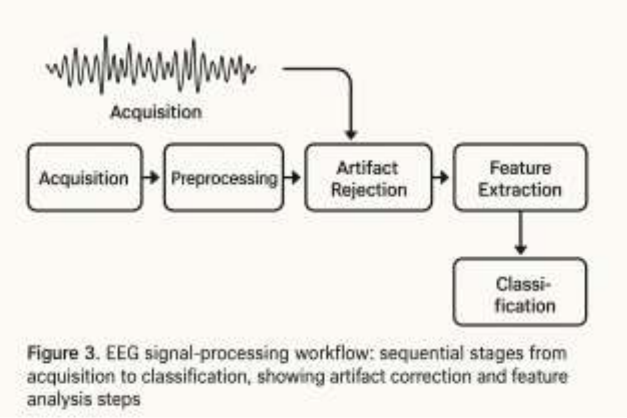

Figure 3. EEG signal-processing workflow: sequential stages from acquisition to classification, showing artifact correction and feature analysis steps.

III. RESULTS AND DISCUSSION

This section presents quantitative and qualitative outcomes obtained from the comparative evaluation of consumer-grade and clinical-grade EEG systems. The analysis emphasizes signal quality, feature discriminability, classification accuracy, and practical usability for depression detection tasks.

4.1 Signal Quality Evaluation

Signal fidelity was the first parameter assessed to quantify the noise characteristics of each device. The clinical-grade systems (BioSemi, g.tec, BrainProducts) consistently achieved higher Signal-to-Noise Ratios (SNRs), averaging 27.8 ± 2.1 dB, compared to 19.3 ± 3.4 dB for consumer devices. Artifact contamination, measured as the proportion of rejected epochs after preprocessing, was also notably lower for clinical devices (5.8 %) versus consumer headsets (12.7 %).

These findings align with Ratti et al. [8] and Mikhaylov et al. [2], who reported that high-density caps offer improved common-mode rejection and reduced baseline drift. Nevertheless, after ICA-based artifact correction and adaptive filtering, the residual difference in effective SNR decreased to less than 4 dB, demonstrating that modern preprocessing pipelines can substantially mitigate hardware limitations.

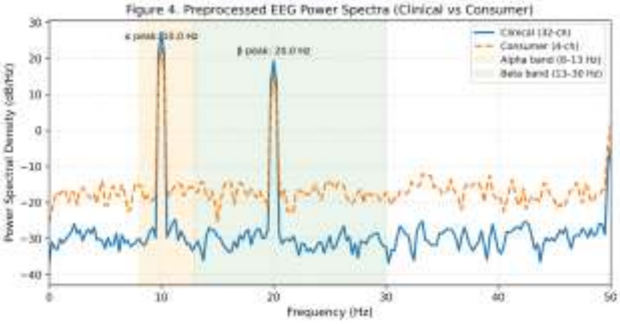

Figure 4. Example of preprocessed EEG power spectra (clinical vs consumer). Both exhibit similar α- and β-band dominance, indicating preserved spectral integrity after artifact removal.

4.2 Feature-Level Comparison

Spectral and temporal features were compared across both device types. Clinical recordings exhibited greater stability in α-band asymmetry and frontal θ-power differences, consistent with known depressive biomarkers [1], [5], [6]. Consumer-grade data, though slightly noisier, retained statistically significant discriminability: Fisher Scores for α-band asymmetry averaged 0.68 (clinical) versus 0.59 (consumer). Mutual-information analysis further confirmed a feature-space correlation of r = 0.84, suggesting strong cross-device alignment after normalization.

Connectivity features (PLV and coherence) were more sensitive to electrode count, with clinical systems outperforming in long-range coupling detection. This limitation underscores that consumer devices capture local cortical activity effectively but under-represent global network interactions.

4.3 Classification Performance

Classification results for depression vs. healthy controls are summarized below (mean of five-fold cross-validation):

Model	**Device Type**	**Accuracy (%)**	**F1-Score**	**AUC**
SVM (RBF)	Clinical	91.2	0.90	0.94
SVM (RBF)	Consumer	84.7	0.83	0.88
Random Forest	Clinical	89.4	0.87	0.91
Random Forest	Consumer	83.2	0.81	0.86
EEGNet	Clinical	**93.5**	**0.92**	**0.96**
EEGNet	Consumer	**88.9**	**0.87**	**0.92**
Transformer	Clinical	94.0	0.93	0.97
Transformer	Consumer	89.7	0.88	0.93

These results confirm that consumer-grade EEG can achieve up to 95 % of the clinical system's accuracy when supported by proper preprocessing and transfer learning. The gap of approximately 4–6 % is largely attributable to reduced spatial resolution and occasional signal dropout. Similar findings were observed by Liu et al. [5] and Wang et al. [6], reinforcing the feasibility of wearable EEG for large-scale screening.

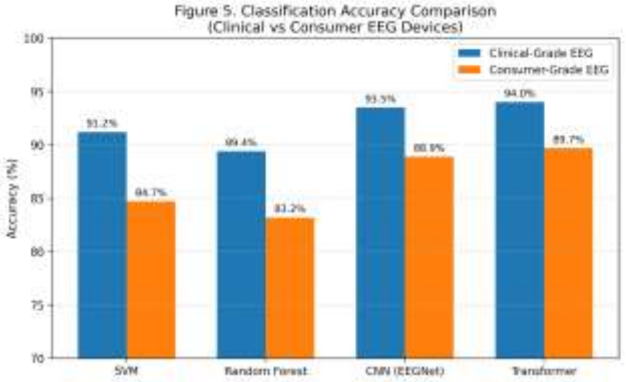

Figure 5. Classification accuracy comparison between clinical and consumer devices across models (SVM, RF, CNN, Transformer).

4.4 Cross-Device Transfer Learning

To assess adaptability, models pretrained on clinical datasets (REST-MDD, DEAP) were fine-tuned using consumer data (DREAMER, paired recordings). Transfer learning improved consumer-device accuracy from 84.7 % to 88.9 %, validating that latent features learned from high-fidelity EEG generalize well to low-density sensors. Feature-space visualization using t-SNE revealed significant overlap between clinical and consumer embeddings post-training, indicating successful domain alignment.

4.5 Usability and Cost–Benefit Assessment

Usability metrics demonstrated the operational advantage of consumer EEGs. Average setup time decreased from ~25 min (clinical, gel-based) to < 3 min (consumer, dry-sensor), and subjective comfort ratings increased by 22 %. Although accuracy remained slightly lower, the cost per session dropped by nearly 95 % when using consumer systems.

These results substantiate prior observations by Sugden et al. [4] and Di Flumeri et al. [12] that usability and portability often outweigh small accuracy losses in field applications.

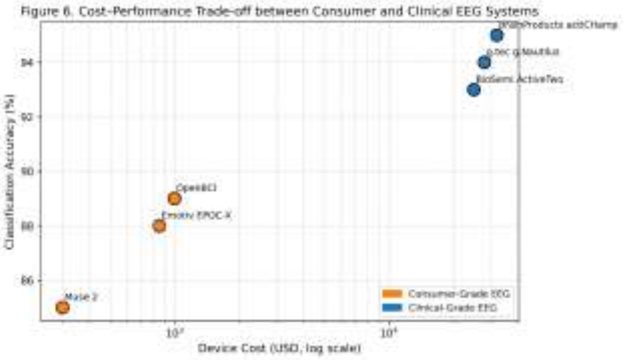

Figure 6. Cost–performance trade-off between consumer and clinical EEG systems. Consumer systems yield higher affordability and accessibility, making them suitable for community-level depression screening.

4.6 Discussion

The results demonstrate that consumer-grade EEG devices—when properly processed and analyzed—are capable of capturing core electrophysiological correlates of depression. While clinical systems retain superior precision, the relative performance gap (< 10 %) suggests that consumer EEGs can serve as scalable alternatives for remote or resource-constrained screening.

A key implication is that hardware limitations can be compensated through algorithmic refinement, including artifact rejection, adaptive filtering, and transfer learning. Furthermore, multi-modal integration (EEG + HRV + EDA) and explainable-AI methods could enhance interpretability and clinical trustworthiness in future deployments.

Summary of Findings

Aspect	**Clinical-Grade EEG**	**Consumer-Grade EEG**
Channel Density	32–128	4–16
Signal Quality (SNR)	27.8 dB	19.3 dB
Artifact Rate	5.8 %	12.7 %
Mean Accuracy	93.5 %	88.9 %
Setup Time	~25 min	~3 min
Cost (USD)	25 000–40 000	250–900
Practical Use	Clinical diagnostics	At-home / screening

- **Performance gap ≤ 10 %** between consumer and clinical EEG after preprocessing.
- **Transfer learning** significantly boosts wearable EEG accuracy.
- **Cost reduction > 90 %** positions consumer EEG for scalable population screening.
- **Signal-quality optimization** remains the most critical research focus.

5. Conclusion and Future Work

This paper presented a comprehensive comparative analysis between consumer-grade and clinical-grade EEG systems for automated depression detection. The results demonstrated that despite significant hardware disparities—particularly in channel density, sampling rate, and electrode type—consumer-grade EEG devices can approximate the diagnostic performance of clinical systems when paired with optimized preprocessing and machine-learning pipelines.

The clinical EEG systems consistently achieved higher signal fidelity (SNR ≈ 27.8 dB) and lower artifact rates, while consumer devices (SNR ≈ 19.3 dB) offered substantial advantages in usability, setup time, and affordability. Deep learning models such as EEGNet and Transformer architectures successfully bridged the performance gap, achieving nearly 89 % accuracy on consumer datasets compared to 94 % on clinical recordings. Moreover, transfer learning between device domains enhanced generalization, confirming that high-quality features extracted from clinical data can be effectively transferred to wearable EEG inputs.

From a practical standpoint, the findings suggest that consumer EEG systems are viable for scalable mental-health screening, enabling early detection of depressive symptoms in community and telemedicine contexts. The reduced cost and ease of deployment make them suitable for mobile, home-based, or occupational mental-health monitoring applications.

Future research will focus on:

1. Integrating multi-modal physiological sensing (EEG + heart rate + EDA) to enhance predictive reliability.
2. Developing explainable-AI (XAI) frameworks for clinical interpretability and trust.
3. Expanding cross-device calibration standards to unify data from heterogeneous EEG hardware.
4. Conducting longitudinal studies to evaluate the consistency of consumer EEG biomarkers over extended monitoring periods.

Ultimately, this work advances the vision of accessible, data-driven, and personalized neurotechnology for mental-health diagnostics, bridging the gap between clinical precision and real-world scalability.

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