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Real-Time Positive Emotion Recognition Using the Positive Unlabeled Learning Method in a Brain Computer Interface System

Zizhu Li[1], *Chengyuan Shen*[2], *Liangyu Zhao*[3], *Taiyo Maeda*[1],*and Jianting Cao*[1,4]

[1]Graduate School of Engineering, Saitama Institute of Technology, Fukaya 369-0217, Japan

[2]Keio University, Yokohama, Kanagawa 223-8522, Japan

[3]More & More Co., Ltd, Zushi, Kanagawa 249-0006, Japan

[4]RIKEN Center for Advanced Intelligence Project(AIP), 103-0027, Japan

Email addresses {i3003lqa, maedat, cao}@sit.ac.jp

chengyuanshen@keio.jp

zhao@momore.co.jp

Correspondence: cao@sit.ac.jp

Abstract

Precise identification of emotional states is critical for affective computing applications—ranging from adaptive human–computer interfaces to clinical mental-health assessments. Traditional vision-based systems, however, lose effectiveness when facial expressivity is compromised (e.g., in Alzheimer's or Bell's palsy), driving interest in Electroencephalography (EEG)-based approaches. Yet, assembling large, reliably labeled EEG emotion datasets remains a major hurdle. To address this, we introduce a Brain–Computer Interface (BCI) framework that employs Positive–Unlabeled learning, training on a small, labeled subset alongside sufficient unlabeled data for preliminary evaluation. Coupled with a low-cost, portable EEG headset, our design minimizes equipment complexity without sacrificing performance. Validation shows an offline classification accuracy of 86.77% and a 86.20% success rate in real-time trials, confirming the method's robustness and applicability.

Keywords: EEG, PU learning, emotion recognition

Introduction

Positive affect represents complex cerebral reactions to external stimuli, and decoding these responses holds promise for numerous practical applications. Research in emotion classification has surged, driven by its capacity to optimize human–computer interfaces, refine psychological assessments, and aid those facing communication impairments. In particular, positive emotional states play a pivotal role in health: they foster mental resilience, mitigate symptoms of depression and anxiety, and even bolster immune performance and general physiology. Consequently, precise detection of positive affect across varied populations is essential Alexander et al., 2021.

Conventional vision-based methods infer emotional states by analyzing facial muscle activity. However, their reliability drops sharply when facial mobility is compromised—for instance, among elderly nursing-home residents, Alzheimer's patients, or individuals with Bell's palsy—because impaired musculature disrupts the transmission of emotional cuesTamata and Mohammadnezhad, 2023, rendering expression-based systems unsuitable for these groups, however, our approach has potential applicability to such populations, which will be validated in future studies.Kumari et al., 2015.

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To overcome these drawbacks, researchers increasingly turn to EEG-based approaches for emotion detection. By capturing neuronal activity directly, EEG bypasses the pitfalls of facial-expression methods. As a result, a variety of machine-learning algorithms have been tailored to interpret EEG patterns, driving notable progress in affective computingPan and Zheng, 2021Özerdem and Polat, 2017Abdulrahman et al., 2022.

When large labeled EEG datasets are available, deep neural networks have been shown to uncover intricate data patterns for highly accurate emotion classification Zhang et al., 2020. However, assembling extensive, reliably annotated emotional EEG corpora is both laborious and costly, since it relies on experts to manually label affective states. Recent studies on PU learning have demonstrated its effectiveness in text classification, biomedical applications, and EEG-based tasks Zhao et al., 2018M. Du Plessis et al., 2015; M. C. Du Plessis et al., 2014; Kiryo et al., 2017. However, few works have explored its integration into real-time BCI systems. Positive–Unlabeled (PU) learning Zhao et al., 2018 addresses this challenge by training a binary classifier on a small set of confirmed positive samples alongside a much larger pool of unlabeled data that includes both positive and non-positive instances. This semi-supervised strategy enables effective detection of specific emotions—such as positive affect—with far fewer labeled examples Alhalaseh and Alasasfeh, 2020Sohaib et al., 2013Zhong et al., 2020Wang et al., 2018.

BCI systems translate neural activity into commands for interacting with external devices Wolpaw, 2013. Yet, their deployment faces hurdles due to the high expense and operational complexity of standard EEG rigs. Although research-grade EEG setups deliver superior spatial resolution and signal fidelity, their cost and maintenance needs limit real-world use. To address this, we adopted the Muse portable EEG headset—a low-cost, plug-and-play solution that streams brain signals in real time, enabling flexible data collection across varied environments. While the Muse's signal quality and signal-to-noise ratio fall short of clinical-grade devices Ratti et al., 2017, its affordability and ease of use make it an excellent platform for practical BCI studies.

In this study, we developed a BCI platform for real-time positive affect detection using a PU-learning framework. Validation proceeded in two phases: offline training and live testing. During the offline stage, EEG signals acquired via the Muse headset were combined with the SEED dataset, and differential entropy features from five participants were used to train a PU-based classifier. After confirming its performance in offline trials, we integrated the model into a real-time pipeline: streaming Muse EEG data, extracting DE features on the fly, and classifying emotional states. The system consistently achieved high accuracy in detecting positive affect, demonstrating the PU learning approach's effectiveness in both retrospective and online settings.

Methodology

PU Learning for Classification In this study, we employ the Unbiased Risk Estimator (URE)-based PU learning framework M. Du Plessis et al., 2015; M. C. Du Plessis et al., 2014; Kiryo et al., 2017. This method was selected because it provides a theoretically sound estimation of classification risk without requiring negative labels.PU learning addresses scenarios where only a fraction of the dataset carries positive labels, while the remainder is entirely unlabeled. In contrast to conventional supervised techniques that require annotations for every class, PU methods leverage a sparse set of confirmed positives together with abundant unlabeled samples. Unlike typical semi-supervised learning, PU learning does not demand any negative labels.

Fundamentally, PU learning reframes the problem as a two-class task—positive versus negative—by exploiting positive instances and unlabeled data. Current algorithms fall into two main families based on their treatment of the unlabeled pool. The first family focuses on extracting a subset of highly reliable positives from the unlabeled data, after which off-the-shelf binary classifiers can be trained on the resulting labeled set Blum and Mitchell, 1998Liu et al., 2002X. Li and Liu, 2003. The second family regards the unlabeled examples as a mixture of positives and negatives, assigning probabilistic weights to reflect their likelihood of being positive during model fitting Liu et al., 2003Elkan and Noto, 2008Lee and Liu, 2003.

Let x represent the input feature vector extracted from one EEG segment, and let $y \in \{\pm 1\}$ denote the class label, where $+1$ indicates a Positive signal and -1 represents a Non-Positive signal. The class-conditional distributions are defined as:

$$\begin{aligned} p_p(x) &= p(x \mid y = +1), \\ p_n(x) &= p(x \mid y = -1). \end{aligned} \tag{1}$$

The prior probabilities for each class are $\pi_p = p(y = +1)$ and $\pi_n = p(y = -1) = 1 - \pi_p$. In PU learning, we assume that π_p is known in advance. Using Bayes' theorem, the marginal distribution of the unlabeled data $p(x)$ can be expressed as:

$$p(x) = \pi_p p_p(x) + \pi_n p_n(x). \tag{2}$$

To address the PU learning problem, we utilize the empirical unbiased risk estimator proposed by M. Du Plessis et al., 2015; M. C. Du Plessis et al., 2014; Kiryo et al., 2017:

$$\hat{R}_{pn}(g) = \pi_p \hat{R}_p^+(g) + \pi_n \hat{R}_n^-(g), \tag{3}$$

Here, $\hat{R}_p^+(g)$ and $\hat{R}_n^-(g)$ denote the empirical risk computed over positive and non-positive samples, respectively. The mapping $g(\cdot)$ refers to the binary decision function, and$l(g(x), y)$ specifies the loss metric. Accordingly, the empirical risks are given by:

$$\begin{aligned} \hat{R}_p^+(g) &= \mathbb{E}_{x \sim p_p(x)} l(g(x), +1), \\ \hat{R}_n^-(g) &= \mathbb{E}_{x \sim p_n(x)} l(g(x), -1). \end{aligned} \tag{4}$$

However, since we only have labels for Positive signals, the distribution $p_n(x)$ and thus $\hat{R}_n^-(g)$ cannot be computed directly. From the relationship in equation (2), we can express the Non-Positive distribution as:

$$\pi_n p_n(x) = p(x) - \pi_p p_p(x). \tag{5}$$

Therefore, the empirical risk for Non-Positive samples can be calculated by:

$$\pi_n \hat{R}_n^-(g) = \hat{R}_u^-(g) - \pi_p \hat{R}_p^-(g), \tag{6}$$

Here, $\hat{R}_u^-(g)$ and $\hat{R}_p^-(g)$ denote the empirical risk evaluated under the overall marginal distribution $p(x)$ and the positive-sample distribution $p_p(x)$,respectively. They are formally defined as:

$$\begin{aligned} \hat{R}_u^-(g) &= \mathbb{E}_{x \sim p(x)} l(g(x), -1), \\ \hat{R}_p^-(g) &= \mathbb{E}_{x \sim p_p(x)} l(g(x), -1). \end{aligned} \tag{7}$$

Hence, the estimator for the risk in Equation (3) can be indirectly expressed as follows:

$$\hat{R}_{pu}(g) = \pi_p \hat{R}_p^+(g) + \hat{R}_u^-(g) - \pi_p \hat{R}_p^-(g). \tag{8}$$

In PU learning, any binary classifier $g(x)$ —from Linear Discriminant Analysis to Support Vector Machines—can serve as the decision function. In this work, we select Random Forests (RF) for $g(x)$ due to their robustness in small-sample EEG classification. The number of trees was set to 100 based on preliminary trials and prior studies Özerdem and Polat, 2017Alhalaseh and Alasasfeh, 2020. The prior probability π_p was set to 0.3 following established practices in PU learning M. Du Plessis et al., 2015; M. C. Du Plessis et al., 2014; Kiryo et al., 2017. Accordingly, rather than using gradient-based optimization, we adapt RF's ensemble-based training to directly optimize the PU objective in Equation (9). An overview of the PU learning workflow appears in Figure 1, and the step-by-step procedure is summarized in Table 1.

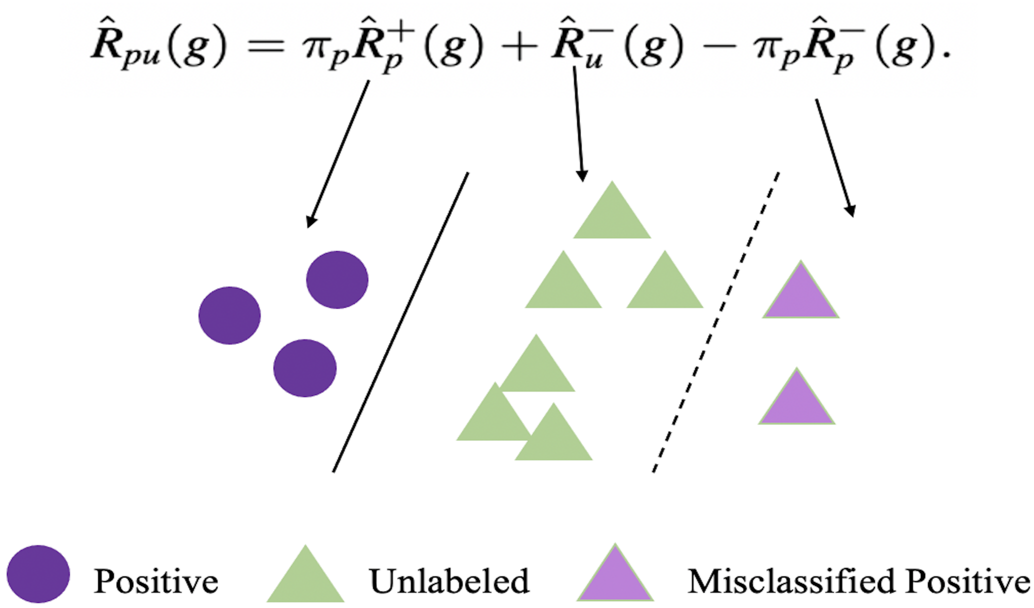

Fig. 1 The algorithmic visualization of PU learning, illustrates how each component of the risk estimation formula correlates with different data types: positive (purple circles), unlabeled (green triangles), and misclassified positive (purple triangles).

Table 1. PU Learning Algorithm.

Algorithm: PU Learning Algorithm
Input: Data set with labeled positive samples and unlabeled samples.
Initialization: Initialize classifier function g, set initial priors π_p, and define loss functions l.
Output: Risk estimates $\hat{R}_{pu}(g)$ and classifier model parameters.
While the convergence condition is not met: • Update Positive Risk Estimate $\hat{R}_p^+(g)$ via Equation (4) • Update Unlabeled Risk Estimate $\hat{R}_u^-(g)$ via Equation (7) • Update Misclassified Positive Risk Estimate $\hat{R}_p^-(g)$ via Equation (7) • Update Classifier: Adjust parameters of g based on updated risk estimates • Check Convergence: Evaluate if the reduction in risk estimates is below a predefined threshold using Equation (8)

The algorithm outlines the iterative PU learning process for risk-based model optimization.

Dataset and Feature extraction In addition to the publicly available SEED dataset, we also constructed an in-house dataset using a lightweight portable EEG device (Muse). The recording procedure, including the use of emotion-inducing film clips, self-assessment labeling, and experimental environment, was designed to be consistent with the SEED dataset, thereby ensuring comparability between the two datasets. Emotion-inducing stimuli included short movie clips and music excerpts validated in prior affective computing studies. After each trial, participants provided self-assessment ratings of their emotional state, which were reviewed by two independent experts to confirm label reliability. All experiments were conducted in a sound-attenuated room with subjects seated comfortably.

A total of fifteen film clips (positive, neutral, and negative) were chosen as stimuli, based on the following criteria: (a) the overall experiment duration should not induce subject fatigue; (b) the content should be easily understood without additional explanation; and (c) each clip should predominantly elicit a single target emotion. Each film clip lasted approximately 4 minutes and was edited to maximize emotional coherence and salience. The details of the film clips used are summarized in Table 2. Each experimental session consisted of 15 trials. Before each clip, a 5-second cue was presented, followed by the 4-minute film stimulus. Afterward, participants were given 45 seconds to complete a self-assessment questionnaire and 15 seconds to rest before the next trial. To avoid emotional carryover, film clips targeting the same emotion were not shown consecutively.

We sourced data from the SJTU Emotion EEG Dataset (SEED) (https://bcmi.sjtu.edu.cn/home/), applying a 0.05–50 Hz band-pass filter to all recordings. From the 62-channel recordings of 15 participants, we randomly retained 12 subjects for our experiments. Given evidence that positive affect elicits strong responses in the lateral temporal cortex, we extracted signals from four electrodes in this region to streamline real-time processing. Prior work has shown that focusing on a targeted subset of channels can outperform full-montage analyses—for instance, a Deep Belief Network trained on these four sites achieved an average classification accuracy of 82.88% Zheng and Lu, 2015. Finally, EEG epochs were one second long, with the preprocessed data sampled at 200 Hz.

To ensure comparability, the Muse recordings adopted the same stimulus paradigm and labeling procedure as SEED. Moreover, the four Muse electrodes correspond to the subset of lateral temporal and frontal electrodes extracted from SEED, thereby aligning the portable device recordings with the channel configuration validated in the benchmark dataset.

Table 2. Film clips used as emotion-inducing stimuli in the in-house dataset.

Emotion	Film Source	Clip Duration (hh:mm:ss)
Neutral	*World Heritage in China* (documentary)	Ep.2 (00:00:50–00:04:36; 00:10:40–00:13:44); Ep.13, Ep.30 (long segments)
Negative	*Aftershock* (disaster drama) *Back to 1942* (historical drama)	00:20:10–00:23:35; 01:48:53–01:52:18 00:49:58–00:54:00; 02:01:21–02:05:21; 02:16:37–02:20:37
Positive	*Lost in Thailand* (comedy)	00:06:13–00:10:11; 01:05:10–01:08:29; 01:17:33–01:21:18; 01:27:25–01:31:05; 01:33:22–01:36:25

Each clip was selected based on its capacity to evoke consistent emotional responses across participants.

Summary and Workflow In our offline experiments, each 1-second EEG epoch is treated as an independent training sample. We first apply a band-pass filter to these epochs, then derive a set of features—most notably Differential Entropy (DE)—to represent the neural activity. Comparative evaluations showed that DE consistently produced the highest classification accuracy. Finally, by using a limited set of positively labeled epochs, we train a PU-learning classifier to distinguish positive from non-positive emotional states Z. Li et al., 2024.

Based on the model trained during the offline setting, we are able to perform real-time classification of emotions into Positive and Non-positive categories. This enables effective and immediate emotion recognition, which is essential for applications that depend on adapting to the user's emotional state in real-time. Our online setting and offline workflow is illustrated in Figure 2.

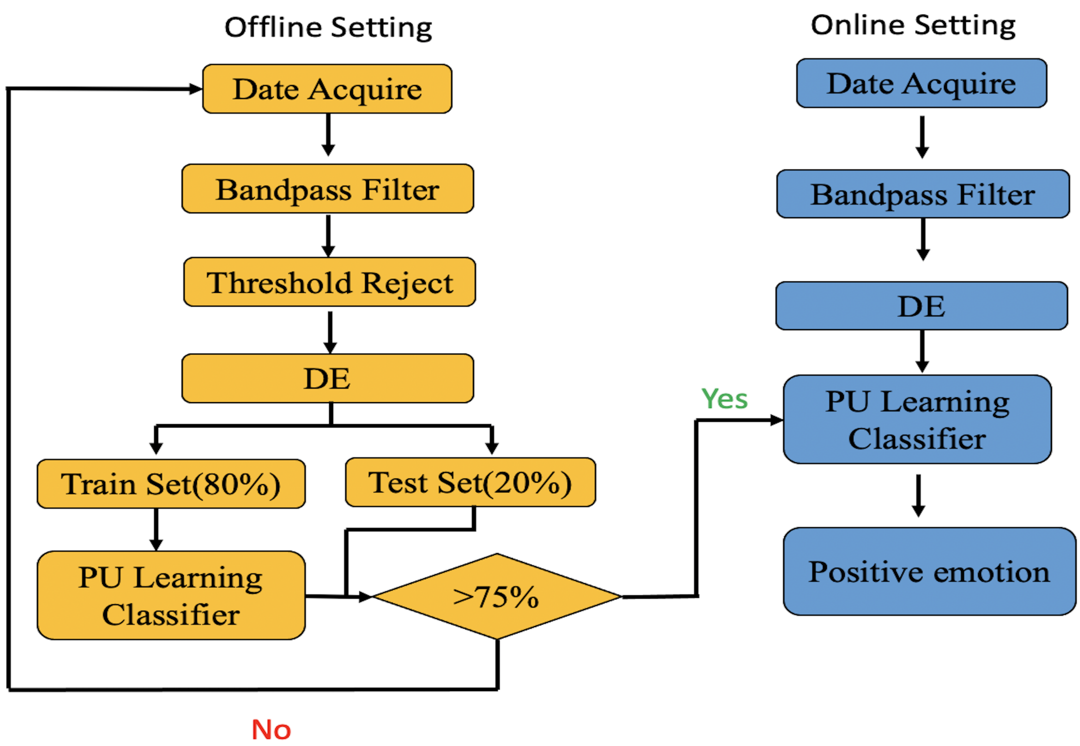

Fig. 2 Workflow for classifying positive versus non-positive emotional signals in offline and online settings.

Experimental Results

Offline experimental and its results In these experiments, we merged the SEED dataset with an in-house EEG corpus—augmented by synchronized video annotations—and applied a 0.05–50 Hz band-pass filter to all recordings. We first partitioned the SEED dataset, allocating 80% of the samples for PU-based training and the remaining 20% for testing. Positive instances were randomly sampled and assigned positive labels, while the rest were treated as unlabeled. For iterative PU training, we initially assumed all unlabeled samples as negatives, forming a provisional negative pool. At each iteration, 100 of these provisional negatives were reclassified as pseudo-positives, progressively refining the training distribution. Random Forest hyperparameters were manually configured and kept fixed across all runs.

To evaluate robustness, we conducted 70 iterative trials.In this extended protocol, Muse-acquired EEG data were incorporated into the training pool together with SEED data. This unified setup allowed us to expand the dataset and assess the robustness and stability of the proposed approach under a larger training corpus. As illustrated in Figure 3, the classifier's performance was tracked across 70 iterations using F1 score, Precision, and Recall. The curves demonstrate a consistent trend: Precision remained high throughout, Recall gradually declined as more pseudo-positives were introduced, and F1 score exhibited a balanced trade-off between the two. This result highlights the robustness of the PU-based framework under progressive reclassification. Furthermore, Figure 4 shows the AUC trajectory, providing a threshold-independent evaluation of classification stability.in addition to the iterative evaluation, we further compared the proposed PU-learning framework against several baseline classifiers widely used in EEG-based emotion recognition, including Support Vector Machine (SVM), Random Forest (RF). Table 3 summarizes the comparative results in terms of classification accuracy.

Table 3. Accuracy comparison of PU learning with baseline models.

Method	**Accuracy**
PU Learning (ours)	0.8677
SVM	0.8123
Random Forest	0.8350

The proposed PU learning method achieved the highest classification accuracy compared with conventional models.

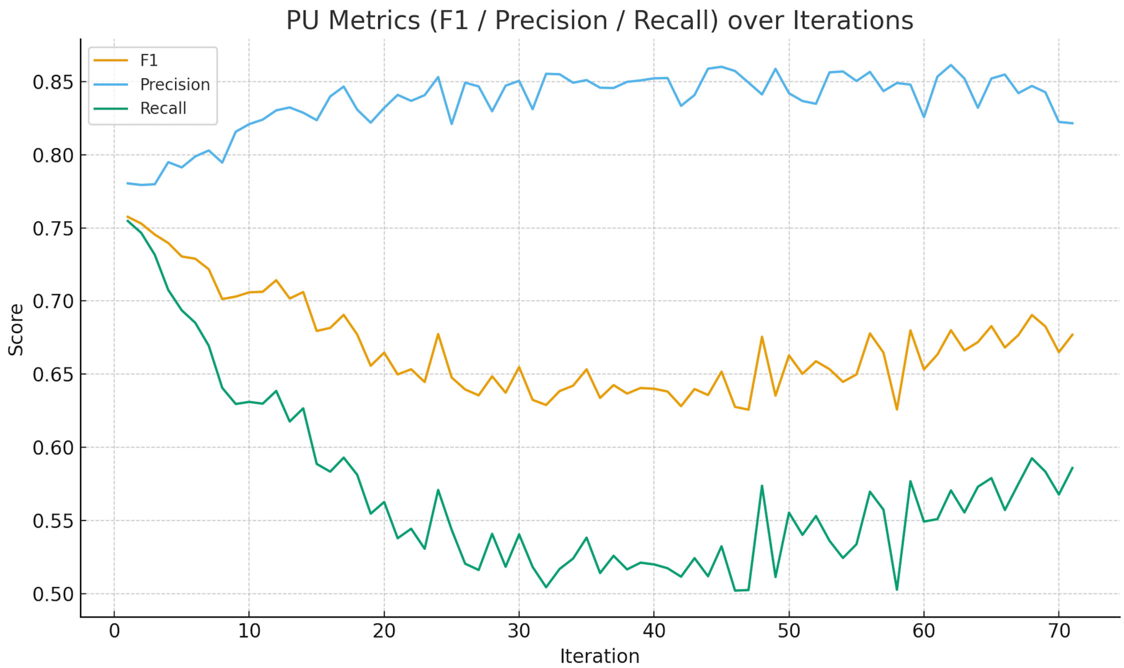

Fig. 3 Accuracy comparison of PU learning with baseline models.

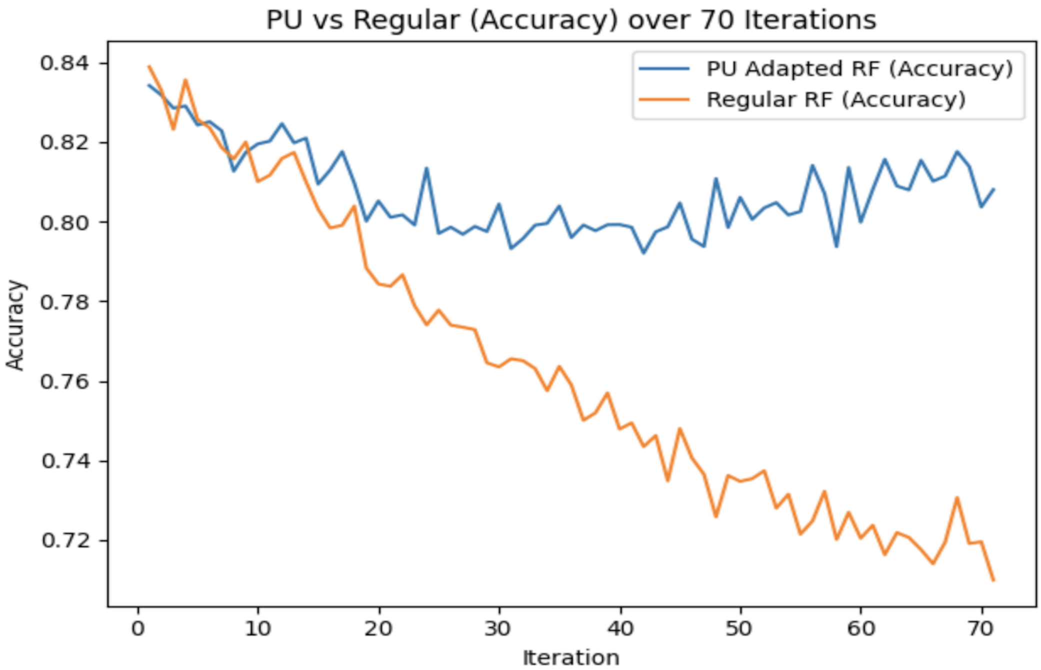

Fig. 4 Accuracy after 70 iterations.

Online experimental and its results Prior to commencing the real-time Online experiment, we selected the PU learning model with the highest accuracy after 70 iterations from the offline experiments and saved it as the Online PU learning classifier. The real-time input data were subjected to a band-pass filter ranging from 0.05 to 50 Hz, followed by DE computation. Since the EEG data used during training had a duration of 1 second with a sampling rate of 200

Hz, we maintained the same data format in the design of the Online experiment. The resulting DE features were then input into the trained PU learning classifier for evaluation; specifically, the DE values calculated for each 1-second EEG segment were assessed. If the classification result met the criteria, an output of 1 was generated, indicating successful recognition of positive emotion. Online experimental flowchart As shown in Figure 5.

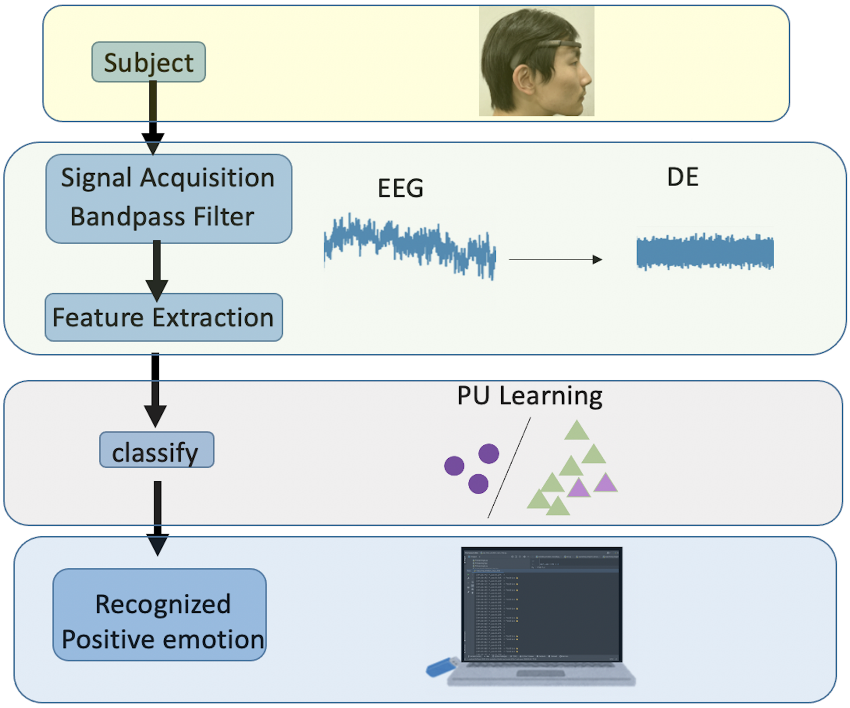

Fig. 5 Online experimental flowchart.

Muse headset electrodes with alcohol wipes. They then donned the device, and electrode impedances were verified using an oscilloscope-based interface to confirm minimal noise in the recordings.

The collected EEG signals underwent band-pass filtering to remove artifacts and extraneous frequency components. Next, Differential Entropy (DE) was calculated by estimating the spectral entropy across the filtered data, yielding feature vectors that capture signal complexity. These DE features were subsequently passed to the PU-learning classifier for emotion inference.

The classifier processed each feature vector and, when its output signaled a positive emotional state, the corresponding trial was marked successful.

We invited five subjects to participate in a total of 500 trials. 431 trials were classified successfully. The online experiment accuracy rate of the five subjects reached 86.20%. The reduced performance compared to offline experiments can be attributed to real-time factors, including device noise, limited electrode coverage, and signal latency. Figure 6 shows part of our experimental results.

```
Processed_data — python real_time_emotion_reco_final.py — 80×24
[13:30:54] P_pos=0.224  →
[13:30:55] P_pos=0.283  → Positive 👍
[13:30:56] P_pos=0.106  →
[13:30:57] P_pos=0.212  →
[13:30:58] P_pos=0.141  →
[13:30:59] P_pos=0.177  →
[13:31:00] P_pos=0.141  →
[13:31:01] P_pos=0.200  →
[13:31:02] P_pos=0.177  →
[13:31:03] P_pos=0.365  → Positive 👍
[13:31:04] P_pos=0.200  →
[13:31:05] P_pos=0.294  → Positive 👍
[13:31:06] P_pos=0.153  →
[13:31:07] P_pos=0.130  →
[13:31:08] P_pos=0.188  →
[13:31:09] P_pos=0.283  → Positive 👍
[13:31:10] P_pos=0.177  →
[13:31:11] P_pos=0.259  →
[13:31:12] P_pos=0.224  →
[13:31:13] P_pos=0.353  → Positive 👍
[13:31:14] P_pos=0.200  →
[13:31:15] P_pos=0.318  → Positive 👍
[13:31:16] P_pos=0.094  →
[13:31:17] P_pos=0.106  →
```

Fig. 6 Part of online experimental results.

Conclusions and Future Work

This study developed a brain–computer interface (BCI) system for real-time positive emotion recognition based on a positive–unlabeled (PU) learning framework. By reformulating positive emotion recognition as a PU task, the proposed method effectively reduces the dependency on large labeled datasets. In offline experiments, an accuracy of 86.77% was achieved by combining SEED and Muse-acquired EEG data, while real-time experiments reached 86.20%, confirming the feasibility of applying PU learning to portable EEG-based systems.

A comparison between offline and online experiments revealed a notable performance gap. The offline setting benefited from stable and noise-free preprocessing, whereas online experiments were affected by device noise, limited electrode coverage of the Muse headset, and processing latency. These findings emphasize the trade-off between portability and accuracy that is intrinsic to real-time BCI systems.

Despite the promising results, several limitations remain. The study involved only five participants, positioning it as a feasibility study rather than a large-scale validation. Furthermore, the proposed framework has not yet been tested on patient populations—particularly those with motor impairments, who represent one of the key target user groups. Future research should therefore include a substantially larger number of participants and extend testing to clinical cohorts to verify robustness and generalizability.

In future work, expanding the framework to multi-class emotion recognition beyond binary positive/non-positive classification will improve its practical utility. Additionally, integrating multimodal physiological signals or incorporating additional lightweight electrodes may help narrow the performance gap between offline and online conditions. Through these advancements, PU-learning-based portable BCI systems could become a practical tool for affective computing and emotional well-being monitoring in everyday environments.

Conflicts of Interest

The authors have no conflict of interest about anything in this article.

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