# Window-Based Feature Representation and Ablation Analysis for EEG-Based Stress Classification

Fi Imanur Sifaunnufus Ms[1] and Fitra Abdurrachman Bachtiar[1*]

[1] Department of Informatics Engineering, Faculty of Computer Science, Universitas Brawijaya, Malang, 65145, East Java, Indonesia
fitra.bachtiar@ub.ac.id

**Abstract.** Stress classification using electroencephalogram (EEG) signals has become an important research direction because EEG can represent changes in brain activity related to psychophysiological conditions. However, EEG signals are non-stationary, and analysis using long observation segments can reduce the ability of the model to capture local temporal variations. To improve the feature representation for stress classification, the SAM40 dataset was used for this study. A 7.5-second temporal resolution was implemented to better capture the data than non-segmented observations. A comparison of two feature sets, Power Spectral Density (PSD only) with its multi-domain combined formulation (PSD, Hjorth parameters, and Higuchi Fractal Dimension) was carried out. Ablation analysis assessed the incorporation of Synthetic Minority Over-sampling Technique (SMOTE), Particle Swarm Optimization (PSO), and stacking ensemble learning. It is discovered that window-based segmentation achieves better performance than non-windowed baselines. An optimal configuration was made using 7.5-second windowing with combined features together with an XGBoost classifier to achieve an accuracy of 0.83. The reduction in feature dimensionality produced by PSO from 288 to 157 was effective, but it was found to be model-dependent on predictive performance. This study's main finding is that a 7.5-second windowing strategy has a strong impact on feature extraction, but optimization for increasing pipeline complexity does not automatically achieve better accuracy.

**Keywords:** EEG, Stress Classification, Windowing, Ablation Analysis

## 1 Introduction

Stress is a multifaceted human physiological and psychological response to stressors that disrupt an individual's physical, mental, and emotional state [1]. In recent years, stress has become a significant issue that affects mental health and overall well-being. The Indonesia National Adolescent Mental Health Survey (I-NAMHS) reported that 34% of students in Indonesia experienced mental health problems within the past year. This finding highlights the importance of developing effective methods for

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stress detection and classification, particularly as many affected individuals also reported suicidal ideation, planning, or attempts [2].

Besides conventional clinical assessments, stress classification can also be conducted using bio signals. Comparative research showed that EEG outperforms ECG and EDA in stress classification [3]. Although EEG-based stress classification has shown significant progress, many previous studies tend to analyze EEG using long observation periods or static recording sessions to maximize accuracy [4]. However, EEG signals are naturally non-stationary, meaning their characteristics can change within short periods of time. As a result, analyzing EEG using long-duration recordings may overlook important local signal patterns. To address this issue, temporal segmentation or windowing has become an important preprocessing technique because it allows models to learn from shorter and more locally stable EEG segments [5]. Nevertheless, the impact of windowing on other stages of the machine learning pipeline, such as feature extraction, data balancing, feature selection, and classifier performance, has not been systematically investigated.

Recent advancements in biomedical signal processing have increasingly explored hybrid deep learning frameworks, transformer architectures, and advanced classification models to capture complex temporal EEG dynamics. While these state-of-the-art methods rely on automated representation learning and complex feature fusion to maximize predictive accuracy, their black-box nature and high computational demands often pose challenges for clinical interpretability. Consequently, there remains a critical need for robust, lightweight, and highly interpretable machine learning frameworks.

To systematically address these gaps, the primary objective of this study is to evaluate the individual and combined impacts of various pipeline components on EEG stress classification. Specifically, this research aims to determine whether a 7.5-second temporal windowing strategy grounded in existing literature demonstrating its optimality for the SAM40 dataset [6]. It improves classification performance compared to a standard non-windowed baseline. Furthermore, the study investigates whether a combined multi-domain representation, incorporating PSD, Hjorth, and Higuchi parameters, outperforms standard PSD-only features in a windowed environment.

Through a comprehensive ablation analysis, this work also examines the efficacy of SMOTE for handling class imbalance, evaluates whether PSO-based feature selection enhances performance or introduces algorithmic redundancy, and determines if a complex stacking ensemble architecture provides tangible benefits over a well-optimized single classifier.

Unlike previous works that aim for maximum accuracy through opaque and resource-intensive models, this study systematically demonstrates that arbitrarily increasing pipeline complexity does not inherently improve performance. Ultimately, the findings provide a streamlined, computationally accessible, and highly interpretable framework for windowed EEG stress classification, specifically highlighting the efficacy of combined multi-domain features utilized with XGBoost without the need for redundant PSO-based reduction.

## 2 Materials and Method

### 2.1 Dataset

This study utilized the pre-processed, clean version of the public SAM40 EEG dataset, which was explicitly developed to support research on the classification of psychophysiological conditions using electroencephalogram signals [7]. The EEG data were recorded using the Emotiv Epoc Flex gel kit with a sampling frequency of 128 Hz. The 32-channel data were recorded during stress-inducing tasks such as the Stroop Color-Word Test, arithmetic solving, and mirror image identification. Original stress levels were rated subjectively from 1 to 10.

In this study, the labels were transformed into a binary classification task. Stress levels from 1 to 5 were categorized as low stress, while stress levels from 6 to 10 were categorized as high stress. To prevent data leakage and avoid overestimating model performance, this study strictly employs a subject independent data splitting strategy. The subjects assigned to the training, validation, and testing sets are completely distinct and mutually exclusive, ensuring that the classification model is rigorously evaluated on its ability to generalize to unseen subjects. The data distribution before and after 7.5 second windowing is presented in Table 1.

### 2.2 Windowing Strategy

Windowing is a fundamental preprocessing technique employed to partition continuous electroencephalogram (EEG) signals into shorter temporal fragments. This approach effectively reduces computational complexity by focusing on discrete and manageable signal segments [8]. Furthermore, the application of a windowing strategy enhances signal quality by mitigating the impact of non-stationary noise and localized artifacts [9]. This study deliberately utilizes non overlapping windows to maintain sample independence and prevent artificial temporal correlation between adjacent segments. This approach ensures a controlled environment for the subsequent ablation analysis and aligns with the objective of maintaining computational efficiency. EEG signal was segmented using a fixed-time window of 7.5 seconds. The selection of this specific duration was informed by the findings of Jadhav [6], who established that a 7.5-second window achieves superior classification accuracy on the same dataset compared to durations of 2.5, 5, and 10 seconds.

### 2.3 Feature Extraction

Feature extraction was performed to transform the EEG window into numerical representations that can be processed by machine learning models. Two handcrafted feature groups were evaluated. The first group was PSD-only, and a combination of PSD, Hjorth parameters, and Higuchi Fractal Dimension. These features were exclusively selected for their computational efficiency and high interpretability. Unlike opaque deep learning extractors, they enable a controlled ablation analysis of their individual contributions under the proposed windowed configuration.

**Table 1.** Distribution of the SAM40 dataset before and after 7.5-second windowing.

| Heading level | Before | | | After | | |
|---|---|---|---|---|---|---|
| | Samples | Low Stress | High Stress | Samples | Low Stress | High Stress |
| Training | 252 | 163 | 89 | 756 | 489 | 267 |
| Validation | 54 | 35 | 19 | 162 | 105 | 57 |
| Testing | 54 | 35 | 19 | 162 | 105 | 57 |
| Total | 360 | 233 | 127 | 1080 | 699 | 381 |

Power Spectral Density (PSD) describes how signal power is distributed across frequency components and is commonly used to extract frequency-domain information from EEG signals [1][10]. In this study, PSD features were extracted using the Welch method, which estimates spectral density by dividing the signal into segments, computing modified periodograms, and averaging them [11]. Hjorth parameters represent time-domain characteristics of EEG signals and consist of activity, mobility, and complexity [12] [13]. Activity reflects signal variance, mobility represents the average frequency tendency of the signal, and complexity describes how much the waveform deviates from a sinusoidal shape.

Higuchi Fractal Dimension (HFD) was also used to measure the complexity and irregularity of EEG signals [14] [15]. The PSD-only representation produced 160 features, while the combined representation produced 288 features. Power Spectral Density was evaluated independently as the foundational baseline, given its status as the established standard in EEG analysis. Hjorth parameters and Higuchi Fractal Dimension were incorporated specifically to assess their synergistic multi domain contributions when combined with Power Spectral Density, rather than being evaluated in complete isolation.

### 2.4 Ablation Scenarios and Classifiers

This study exclusively employs machine learning pipelines to focus the ablation analysis on handcrafted features, placing deep learning comparisons beyond its scope. The ablation systematically evaluates preprocessing and optimization effects using a literature-established 7.5 s window, with specific scenarios detailed in Table 2.

The classification tasks in this study were performed using five algorithms. Random Forest was implemented as a bagging-based tree classifier that utilizes an ensemble of decision trees [16]. XGBoost was used as a gradient boosting classifier that optimizes a regularized objective function [17]. The SVM algorithm was used to determine the optimal separating hyperplane with a maximum margin between classes [18], Logistic Regression functioned as a linear probabilistic classifier [19]. To further enhance predictive performance, a Stacking Ensemble was utilized to aggregate the predictions of multiple base learners through a meta-learner [20].

To ensure transparency and reproducibility, all hyperparameter configurations are strictly documented in Table 3. Rather than exhaustive tuning, models were initialized with robust standard configurations to facilitate fair systematic comparisons and prevent obscuring the intrinsic contributions of the multi-domain features.

**Table 2.** Ablation scenarios used in the 7.5-second window-based experiment.

| Scenario | Feature Rep. | Add Component | Classifier | Purpose |
|---|---|---|---|---|
| S1 | PSD only vs. PSD + Hjorth + Higuchi | None | RF, XGBoost, SVM, LR | Evaluate baseline feature representation on windowed data |
| S2 | PSD only vs. PSD + Hjorth + Higuchi | SMOTE | RF, XGBoost, SVM, LR | Evaluate the effect of class balancing |
| S3 | PSD only vs. PSD + Hjorth + Higuchi | PSO | RF, XGBoost, SVM, LR | Evaluate feature reduction and model-dependent performance |
| S4 | PSD only vs. PSD + Hjorth + Higuchi | SMOTE + PSO + Ensemble | Stacking and base learners | Evaluate whether stacking ensemble improves over single models |

**Table 3.** Hyperparameter configurations for all pipeline components.

| Component | Algorithm | Hyperparameter Configuration |
|---|---|---|
| Classification Models | XGBoost | random_state = 42, use_label_encoder = False, eval_metric = 'logloss' |
| | Random Forest | random_state = 42 |
| | SVM | random_state = 42, probability = True |
| | Logistic Regression | random_state = 42, max_iter = 1000 |
| Ensemble | Stacking Ensemble | Base Estimatiors : RF, XGBoost, SVM<br>Meta-classifier: Logistic Regression<br>Cv = 5, n_jobs = -1 |
| Data Balancing | SMOTE | random_state = 42, k-Neighbors = 3 |
| Feature Selection | PSO (Swarm Setup) | n_particles=42, iters=50, w=0.9, $c_1$=0.5, $c_2$=0.3 |
| | PSO (Fitness Model) | Random Forest (n_estimators=10, random_state=42, n_jobs=-1) |

# 3 Result and Discussion

## 3.1 Effect of 7.5-Second Window-Based Representation

Table 4 compares the nonwindowed baseline against the 7.5 s windowed configurations. The non-windowed baseline utilizing PSD features and Random Forest yielded 0.78 accuracy and a 0.77 F1 score. Implementing the literature supported 7.5 s

windowing strategy [6] notably enhanced classification. A windowed baseline combining features with XGBoost reached 0.80 accuracy and a 0.79 F1 score. Ultimately, the optimal 7.5 s windowed configuration utilizing integrated features and XGBoost without PSO achieved the highest overall performance, recording 0.83 accuracy and a 0.82 F1 score. Table 4 indicates 7.5 s windowing outperforms nonwindowed baselines because temporal segmentation captures localized variations and transient dynamics typically obscured in long duration observations.

### 3.2 Effect of Feature Representation and SMOTE

The first ablation evaluates isolated PSD against combined PSD, Hjorth, and Higuchi features. On windowed data absent SMOTE and PSO, isolated PSD with Random Forest produced 0.802 accuracy and a 0.792 F1 score. The combined representation using XGBoost maintained this 0.802 accuracy while achieving a marginally higher 0.796 F1 score. This confirms PSD provides a strong frequency domain baseline, yet combined representations contribute critical temporal and complexity-based details. Additionally, applying SMOTE enhanced accuracy across several configurations, particularly within the combined feature framework. With SMOTE, the combined feature representation achieved an accuracy of 0.8241 using both Random Forest and XGBoost. However, the F1-score of XGBoost with SMOTE was 0.7871, which was lower than the non-SMOTE best overall F1-score of 0.8188. Therefore, SMOTE is useful as a balancing strategy, but its effect is not always consistent across evaluation metrics. The ablation trend on the 7.5-second windowed data is shown in Fig. 1.

### 3.3 Effect of PSO-Based Feature Selection

Particle Swarm Optimization (PSO) was used to reduce feature dimensionality and evaluate whether feature selection improves performance after windowing. In case of our multi-domain combined feature set, we compressed the dimensionality from 288 to 157 features, which is 45.49% reduction of feature dimensionality. As shown in Table 5, PSO produced different effects depending on the classifier. For Random Forest, SVM, and Logistic Regression, PSO slightly increased the F1-score. However, for XGBoost and LR decrease. This result indicates that PSO is effective for reducing dimensionality, but it does not always improve classification performance.

### 3.4 Single Model and Stacking Ensemble Comparison

The final scenario, summarized in Table 6, evaluates whether stacking ensemble learning improves window-based system performance when combined with SMOTE and PSO. Despite achieving competitive results on the combined feature representation, the stacking ensemble failed to outperform the optimal single XGBoost model operating without PSO. This outcome highlights the prediction robustness of simpler architectures, indicating that under a 7.5 s windowing strategy, increasing model complexity via ensemble methods does not correlate with enhanced performance.

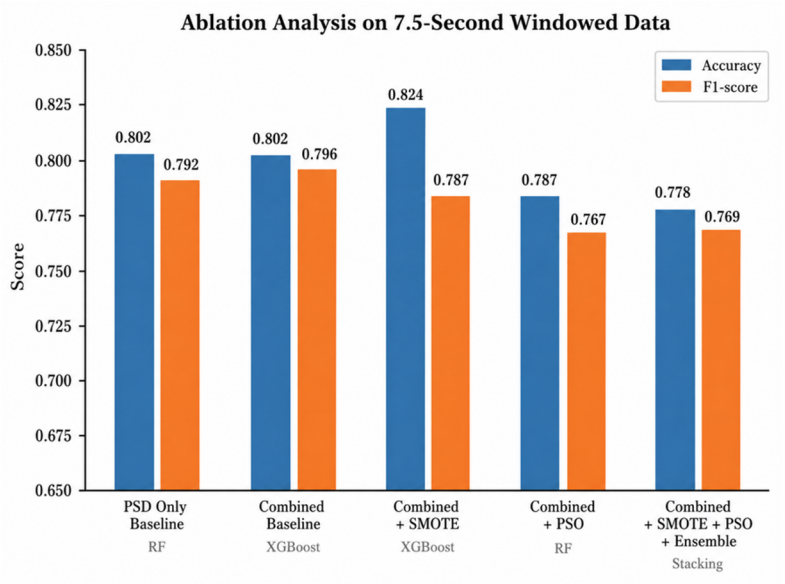



**Fig. 1.** Ablation analysis on 7.5-second windowed data

**Table 4.** Performance comparison between non-windowed and 7.5-second windowed

| Configuration | FSet | Best Model | Acc | Pre | Rec | F1 | Main Finding |
|---|---|---|---|---|---|---|---|
| Non-windowed (Best Overall) | PSD only | RF | 0.78 | 0.77 | 0.78 | 0.77 | Representative baseline before windowing |
| 7.5s windowed | Combined | RF | 0.80 | 0.81 | 0.80 | 0.79 | Windowing improves baseline representation |
| 7.5s windowed + SMOTE | Combined | XGBoost | 0.83 | 0.86 | 0.83 | 0.82 | Best overall configuration without PSO |

FSet = Feature Set; Acc = Accuracy; Prec = Precision; Rec = Recall; F1 = F1-score

**Table 5.** Effect of PSO on the combined feature representation in 7.5-second windowed.

| Model | Before PSO | | | | | After PSO | | | | | Effect |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Fea | Acc | Pre | Rec | F1 | Fea | Acc | Pre | Rec | F1 | |
| RF | 288 | 0.79 | 0.81 | 0.79 | 0.76 | 157 | 0.81 | 0.84 | 0.81 | 0.79 | Slight increase |
| XGBoost | 288 | 0.83 | 0.86 | 0.83 | 0.82 | 157 | 0.80 | 0.81 | 0.80 | 0.78 | Decrease |
| SVM | 288 | 0.71 | 0.72 | 0.71 | 0.66 | 157 | 0.71 | 0.72 | 0.71 | 0.66 | Increase |
| LR | 288 | 0.65 | 0.62 | 0.65 | 0.62 | 157 | 0.64 | 0.61 | 0.64 | 0.62 | Decrease |

Fea = Features; Acc = Accuracy; Pre = Precision; Rec = Recall; F1 = F1-score

**Table 6.** Performance comparison between non-windowed and 7.5-second windowed

| Configuration | FSet | Best Model | Acc | Pre | Rec | F1 | Main Finding |
|---|---|---|---|---|---|---|---|
| Best single model | Combined | XGBoost | 0.83 | 0.86 | 0.83 | 0.82 | Highest overall result |
| Final ensemble scenario | Combined | Stacking Ensemble + SMOTE + PSO | 0.78 | 0.77 | 0.78 | 0.77 | Competitive but lower than best single model |
| Final RF scenario | Combined | RF + SMOTE + PSO | 0.77 | 0.77 | 0.77 | 0.77 | Stable but lower |
| Final XGBoost scenario | Combined | XGBoost + SMOTE + PSO | 0.76 | 0.76 | 0.76 | 0.76 | Lower after PSO |

FSet = Feature Set; Acc = Accuracy; Pre = Precision; Rec = Recall; F1 = F1-score

### 3.5 Discussion

The results identify the 7.5 s window-based representation as the most significant feature, significantly outperforming the non-windowed baseline in accuracy and F1-scores. Shorter EEG segments enhanced the model's ability to capture local temporal patterns and stress-related transient neural dynamics. This balance ensures critical frequency-domain information is retained, while preventing longer windows from diluting the detection of rapid EEG variations.

Furthermore, the synergy among Power Spectral Density (PSD), Hjorth parameters, and Higuchi Fractal Dimension enhanced performance following windowing by providing complementary signal perspectives. Specifically, PSD details frequency domain spectral power, Hjorth parameters capture time domain characteristics, and Higuchi Fractal Dimension offers robust complexity estimation. This multidomain representation proved exceptionally beneficial for XGBoost, maximizing effectiveness by utilizing the complete feature set without requiring additional dimensionality reduction.

A central finding is that increasing pipeline complexity does not inherently improve classification. While SMOTE increased raw accuracy by addressing class imbalance, it failed to consistently enhance F1 scores. Similarly, despite achieving substantial dimensionality reduction, PSO yielded results highly dependent on the classifier. Specifically, the significant XGBoost performance degradation following PSO application exposes a critical algorithmic redundancy. Because XGBoost inherently manages high dimensional data via embedded feature selection during tree construction, prior heuristic reduction by PSO prematurely eliminates synergistic features utilized by gradient boosting. Furthermore, the underperformance of the stacking ensemble reinforces that a single well-matched model is more efficient than complex architectures for the windowed SAM40 dataset.

## 4 Conclusion

This study presented a 7.5 s window-based feature representation and ablation analysis for EEG based stress classification using the SAM40 dataset. This specific duration was selected because existing literature establishes it as optimal for maximizing classification accuracy compared to alternative window sizes. This study evaluates how temporal segmentation affects classification performance and pipeline complexity when integrating multi-domain features, SMOTE, PSO, and ensemble learning. Results show the 7.5 second windowing algorithm significantly improves the classification accuracy compared with the typical non-windowed benchmark. The best configuration combined PSD, Hjorth, and Higuchi features using an XGBoost classifier without PSO, achieving the highest accuracy (0.83), precision (0.86), recall (0.83), and F1-score (0.82). While SMOTE occasionally improved accuracy, it inconsistently affected the F1-score. Furthermore, although PSO effectively reduced feature dimensionality from 288 to 157, its impact on performance remained strictly model dependent. In addition, the stacking ensemble yielded competitive results but eventually did not outperform the best-performing single XGBoost model by being more efficient. Overall, findings demonstrate that a 7.5 s windowing strategy yields a highly discriminative EEG representation for stress classification, proving that optimal performance does not inherently require complex pipelines. Although the strict subject independent validation ensures broad generalization, this study relies on a standardized dataset with controlled electrode placement and session to session variations. Consequently, addressing real world hardware shifts remains a limitation of this offline ablation study and a critical direction for future deployment research.

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