International Journal of Advances in Applied Sciences (IJAAS)
Vol. 15, No. 1, March 2026, pp. 55~64
ISSN: 2252-8814, DOI: 10.11591/ijaas.v15.i1.pp55-64

Performance comparison of feature extraction methods for electroencephalogram-based recognition of Balinese script

I Made Agus Wirawan[1], Ida Bagus Nyoman Pascima[1], Gede Surya Mahendra[1], I Made Candiasa[2], I Nyoman Sukajaya[2]
[1]Undiksha Data Science Research Group, Department of Informatics Engineering, Faculty of Engineering and Vocational, Universitas Pendidikan Ganesha, Singaraja, Indonesia
[2]Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Pendidikan Ganesha, Singaraja, Indonesia

Article Info

Article history:

Received Sep 1, 2025
Revised Nov 10, 2025
Accepted Jan 1, 2026

Keywords:

Balinese script recognition
Brain-computer interface
Differential entropy
Electroencephalogram
Feature extraction

ABSTRACT

Recognizing Balinese script from electroencephalogram (EEG) signals remains a challenging problem due to low signal amplitude, non-stationary dynamics, and significant inter-subject variability. Despite previous attempts, no single feature extraction method has been universally effective in addressing these limitations. To fill this gap, this study systematically evaluates five feature extraction techniques—differential entropy (DE), power spectral density (PSD), discrete wavelet transforms (DWT), Hjorth parameters, and statistical features—on the Balinese imagined spelling using electroencephalography (BISE) dataset, which contains EEG recordings specifically designed for Balinese script recognition. For classification, both artificial neural networks (ANN) and support vector machines (SVM) are applied, and their performance is validated across multiple experimental settings. Results demonstrate that DE consistently provides more stable and discriminative features than the other methods, achieving the highest classification accuracy when combined with ANN. These findings highlight the potential of DE-based approaches to advance electroencephalogram-driven Balinese script recognition, offering a culturally significant contribution to brain-computer interface (BCI) research and supporting future applications in inclusive artificial intelligence, digital heritage preservation, and assistive technologies.

Corresponding Author:

I Made Agus Wirawan
Undiksha Data Science Research Group, Department of Informatics Engineering
Faculty of Engineering and Vocational, Universitas Pendidikan Ganesha
Singaraja, Indonesia
Email: imade.aguswirawan@undiksha.ac.id

1. INTRODUCTION

Modern technological developments aim to create a seamless environment that connects humans and technological devices, supporting daily activities. One typical example of this is speech recognition-based applications, such as Siri and Google Voice Search, which enable direct interaction with electronic devices through spoken commands [1]. Verbal communication disorders can be caused by injuries or neurodegenerative diseases that affect motor control and speech articulation [2]. In more severe cases, such as locked-in syndrome (LIS), sufferers lose almost all motor control, including the ability to speak, making conventional communication impossible [3].

One proposed solution to overcome this limitation is speech imaging, the process of imagining speech without physically articulating it. This concept is part of brain-computer interface (BCI) technology, which connects the brain to an external device by recording and translating brain activity into commands or information [4], [5]. With a mind-to-speech interface, users with motor disabilities can convey messages solely through brain signals, without the need for verbal communication [6]. Various methods have been used to recognize imagined speech patterns, including magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), electrocardiography (ECG), and electroencephalography (EEG) [7], [8]. Among these methods, EEG is considered the most suitable due to its high temporal resolution, low cost, safety, and portability [9]. Despite its advantages, EEG-based imagined speech recognition remains highly challenging, primarily due to the inherently low signal amplitude, non-stationary characteristics, and substantial variability of EEG signals [10], [11]. These conditions complicate the consistent, accurate identification of patterns.

Previous research has proposed three main approaches to feature extraction: the time domain, the frequency domain, and the time-frequency domain. In the time domain approach, methods such as statistical features and Hjorth parameters offer the advantage of simple computation and are suitable for real-time applications [12]. Meanwhile, in the frequency-domain approach, the power spectral density (PSD) and differential entropy (DE) methods have proven effective for extracting wave-frequency-based data patterns. They are widely used in cognitive pattern recognition [10], [13], [14]. In the time-frequency domain approach, the discrete wavelet transform (DWT) method has shown the ability to capture the dynamics of EEG signals in both the time and frequency domains [15]. Thus, selecting the appropriate feature extraction method is a crucial factor in improving the performance of imaginative speech pattern recognition, particularly in *pengangge aksara Bali* (Balinese script), which has unique phonetic and articulatory characteristics. However, previous works on EEG-based imagined speech recognition have primarily focused on international languages, with minimal attention to regional scripts such as Balinese, which possess unique phonetic and articulatory characteristics. To the best of our knowledge, this study is among the first to investigate EEG-based recognition of Balinese script, thereby providing both scientific novelty and cultural significance.

This study aims to address the challenges of EEG-based imagined speech pattern recognition in Balinese script by comparing five feature extraction methods: statistical features, Hjorth parameters, PSD, DE, and DWT. The ultimate goal is to determine the most effective feature extraction method for recognizing imagined speech EEG patterns in Balinese script. The novelty of this study lies in its focus on identifying the most precise feature extraction method for recognizing imagined speech in Balinese script using the Balinese imagined spelling using electroencephalography (BISE) dataset developed in previous research [16]. This study not only makes technical contributions to EEG signal processing but also offers cultural value by supporting the digitization and preservation of under-researched regional languages. The results are expected to address the issues of low EEG signal amplitude and high pattern variability, while also contributing to the development of BCI systems for inclusive artificial intelligence and neurotechnology.

2. METHOD

This research began with processing EEG data from the BISE dataset, including segmentation and artifact removal. The cleaned signals are then decomposed using a band-pass filter to extract four frequency bands. For statistical feature extraction, the Hjorth and DWT parameters use the segmented raw EEG signals. Meanwhile, the DE and PSD methods use the decomposed raw EEG signals, as shown in Figure 1.

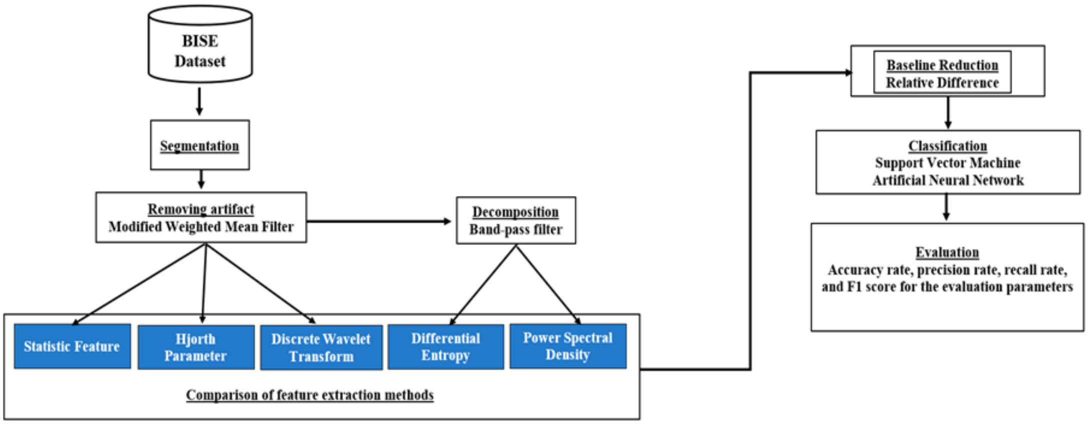

Figure 1. Research stages for determining the appropriate feature extraction method

The resulting features are optimized through a baseline reduction process. The optimized features are then used to classify six classes of Balinese script. To measure model performance, accuracy, precision, recall, and F1-score are evaluated. Each stage of determination in Figure 1 can be described as follows:

i) Stage 1: dataset acquisition. The BISE dataset was obtained from two series of controlled experiments with 31 participants (8 males and 23 females) of Balinese language education students at Universitas Pendidikan Ganesha. EEG recordings were collected using a 32-channel cap based on the international 10-20 system, which includes a rest segment, a character spelling (CS), and a character imagination (CI). This study will use a dataset of six Balinese script spellings (Analysis_character_spelling_trial2). This dataset reflects the script's phonetic diversity and complexity, making it more challenging than a simple alphabet. The dataset is openly accessible in Mendeley Data at https://data.mendeley.com/datasets/c3m4s2dtcr/3 [16]. This dataset, designed as a benchmark for EEG-based BCI research also catalyzes the preservation and digitization of Balinese script, inspiring and motivating the academic community.

ii) Stage 2: signal segmentation. The acquired EEG signals then underwent a segmentation process to separate the baseline and experimental segments [16], [17]. This process aims to obtain baseline and trial signals. The baseline signal was used to reduce the trial signal and was obtained from the first 3 seconds of the experimental signal (joined_data), while the trial signal is obtained from the entire experimental signal (joined_data) [18].

iii) Stage 3: artifact removal. Artifact removal was performed using the modified weighted mean filter (MWMF), which is designed to remove baseline EEG interference. The mathematical equation for the MWMF method is shown in (1) [19].

$$z_j = \left(\frac{\sum_{i=-n}^{n} w_{j+i} x_{j+i}}{(2n+1)\sum_{i=-n}^{n} w_{j+i}}\right) \quad (1)$$

Where n is the window length, and m is the number of data points. The value of j$= n, n+1, n+2, \dots, m+2n$, z_j is the baseline signal amplitude after reduction, x_j is the baseline signal amplitude before reduction, and w_j is the weight value.

iv) Stage 4: signal decomposition. The decomposition stage is performed by applying a fourth-order Butterworth bandpass filter to separate the EEG signal into theta, alpha, beta, and gamma frequency bands [19].

v) Stage 5: feature extraction. Feature extraction is performed to obtain numerical representations of the EEG signal that are relevant to the task at hand. In this stage, five feature extraction methods are compared: statistical features, Hjorth parameters, PSD, DE, and DWT. The best method is selected based on its accuracy in recognizing imaginary speech patterns.

– Statistical features are calculated from the EEG signal x[n] over N samples:

Mean: $\mu = \frac{1}{N}\sum_{n=1}^{N} x[n]$ (2)

Variance: $\sigma^2 = \frac{1}{N}\sum_{n=1}^{N}(x[n]-\mu)^2$ (3)

Standard deviation: $\sigma = \sqrt{\sigma^2}$ (4)

Skewness: $\gamma 1 = \frac{\frac{1}{N}\sum_{n=1}^{N}(x[n]-\mu)^3}{\sigma^3}$ (5)

Kurtosis: $\kappa = \frac{\frac{1}{N}\sum_{n=1}^{N}(x[n]-\mu)^4}{\sigma^4}$ (6)

The statistical method generates 20 features (4 bands×5 statistical methods) for each channel.

– Hjorth parameters

Calculated based on the first and second derivatives of the EEG signal as in (7)-(9).

$$Activity = \sigma_x^2 \quad (7)$$

$$Mobility = \sqrt{\frac{\sigma_{x'}^2}{\sigma_x^2}} \quad (8)$$

Where x' is the first derivative of x.

$$Complexity = \frac{Mobility\ (x\prime)}{Mobility\ (x)} \quad (9)$$

The Hjorth parameter method generates 12 features (4 bands×3 Hjorth parameters methods) for each channel.

– Power spectral density
Using the Welch method as in (10).

$$PSD = \frac{1}{LU}\sum_{i=1}^{L} |FFT(w[n].x_i[n])|^2 \quad (10)$$

Where L is the number of segments, U is the window energy normalization factor, $w[n]$ is the windowing function, $x_i[n]$ is the ith segment of the EEG signal.
The PSD method generates four features (4 bands×1 PSD method) per channel.

– Differential entropy
For a Gaussian signal with variance σ^2 as in (11).

$$DE = \frac{1}{2}log\ (2\pi e\sigma^2) \quad (11)$$

The DE method generates four features (4 bands×1 DE method) for each channel.

– Discrete wavelet transforms
The process of decomposing the EEG signal $x[n]$ into detail coefficients D_j and approximation A_j at level j.
Decomposition:

$$A_j[k] = \sum_n x[n] \cdot g(2k - n) \quad (12)$$

$$D_j[k] = \sum_n x[n] \cdot h(2k - n) \quad (13)$$

where$\cdot g[n]$ is the low-pass wavelet filter and$\cdot h[n]$ is the high-pass wavelet filter.

– Band energy feature extraction:

$$E_j = \sum_k |D_j[\mathrm{k}]|^2 \quad (14)$$

In this study, the db4 wavelet was used, resulting in 16 features (4 bands×4 DWT methods) for each channel [20]. Figure 2 illustrates the workflow of the feature extraction methods, including statistical, Hjorth parameter, and DWT. After segmentation and artifact removal, these three methods extract raw EEG signal features at 1-second intervals from a single channel. The statistical method produces five features: mean, variance, standard deviation, skewness, and kurtosis. The Hjorth parameter method produces three features: activity, mobility, and complexity. The DWT method decomposes the signal into four subbands—approximation 3 (A3), detail 3 (D3), detail 2 (D2), and detail 1 (D1). From each subband, four features are derived: energy, entropy, mean, and standard deviation. Thus, the DWT method produces 16 features per channel for each one-second segment.

Figure 3 illustrates the framework for EEG feature extraction using the DE and PSD methods. Feature extraction is performed after segmentation and artifact removal, followed by signal decomposition into four frequency bands: theta, alpha, beta, and gamma. From each frequency band, both extraction methods are applied to obtain representative features. As a result, each method yields four features per channel for every one-second EEG segment.

vi) Stage 6: baseline reduction. Baseline reduction was performed to generate feature values from the experimental signal that reflect the participant's cognitive or emotional responses. This process uses the relative difference approach as described in the related literature [21], [22].

vii) Stage 7: classification. To evaluate the performance of the feature extraction method, two commonly used classification algorithms for EEG signal analysis were employed: the support vector machine (SVM) and the artificial neural network (ANN). These two methods were chosen based on their frequent use in previous research on EEG signal classification [10], [12].

viii) Stage 8: evaluation. The resulting model was evaluated using the 10-fold cross-validation technique. Performance evaluation was performed using four main metrics: accuracy, precision, recall, and F1-score. The model testing scheme is shown in Figure 4.

Ten model evaluation scenarios are proposed. In each scenario, every feature extraction method is evaluated using both SVM and ANN classifiers. These evaluations produce accuracy, precision, recall, and F1-score values for the six classes of Balinese script characters being recognized.

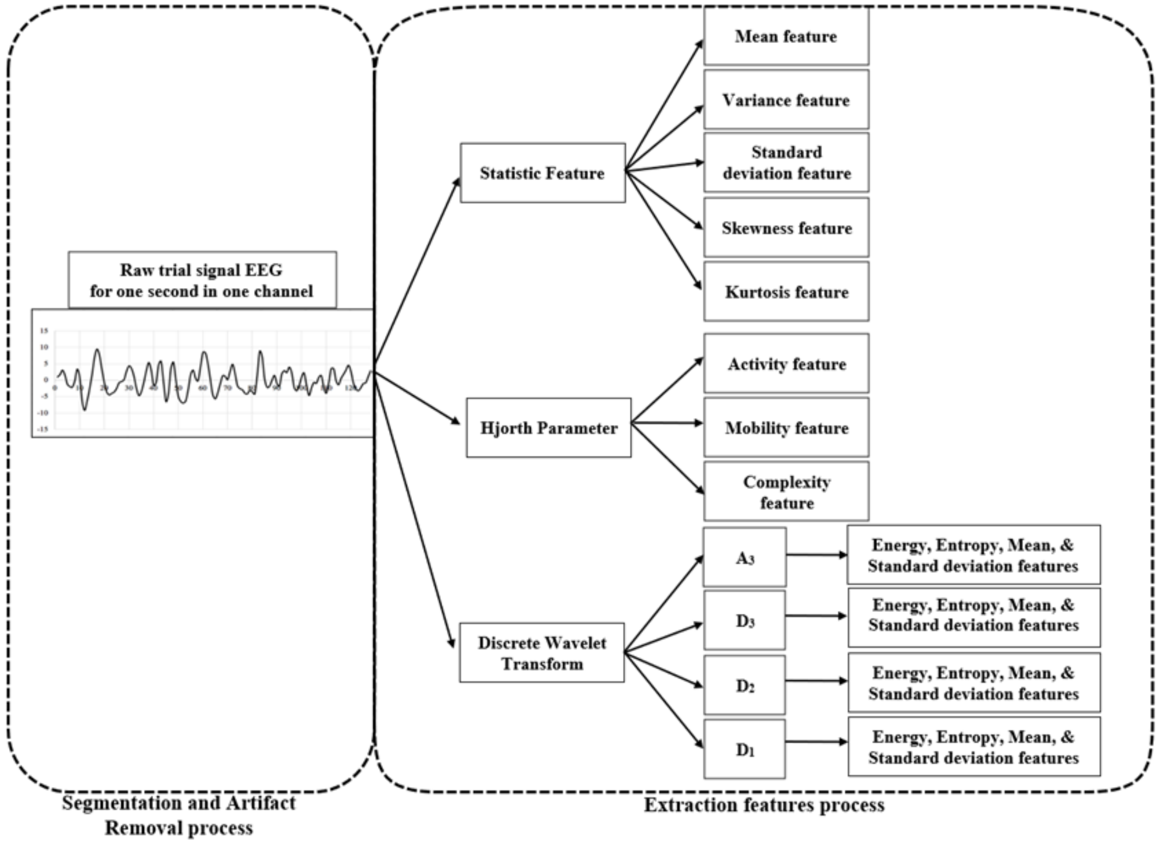

Figure 2. Workflow of the feature extraction methods, including statistical, Hjorth parameter, and DWT

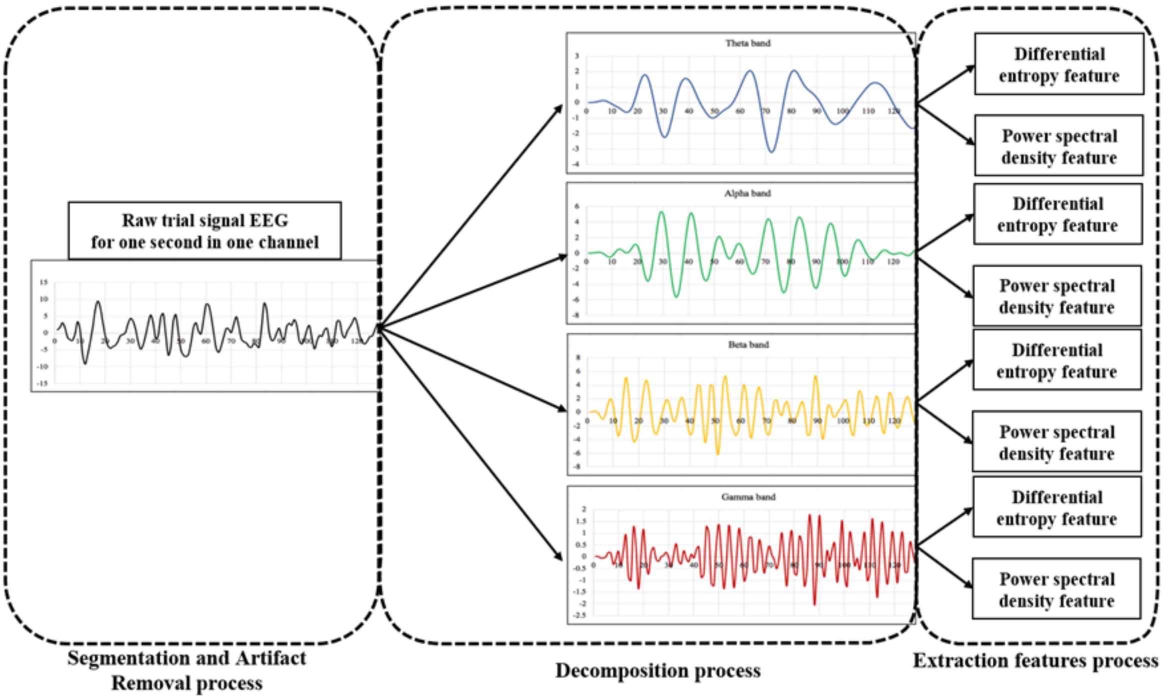

Figure 3. Workflow of the feature extraction methods, including DE and PSD

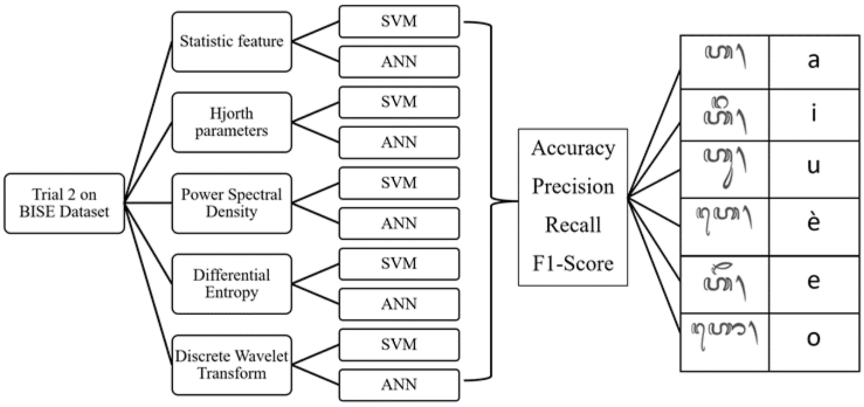

Figure 4. The model evaluation scheme

3. RESULTS AND DISCUSSION

Classification performance was evaluated by comparing five feature types: DE, DWT, Hjorth, PSD, and statistics. The classification process was applied to two different machine learning models: an ANN and an SVM. Figure 5 presents the classification accuracy of the tested features using an ANN. In general, the DE feature yields the highest accuracy among the other features.

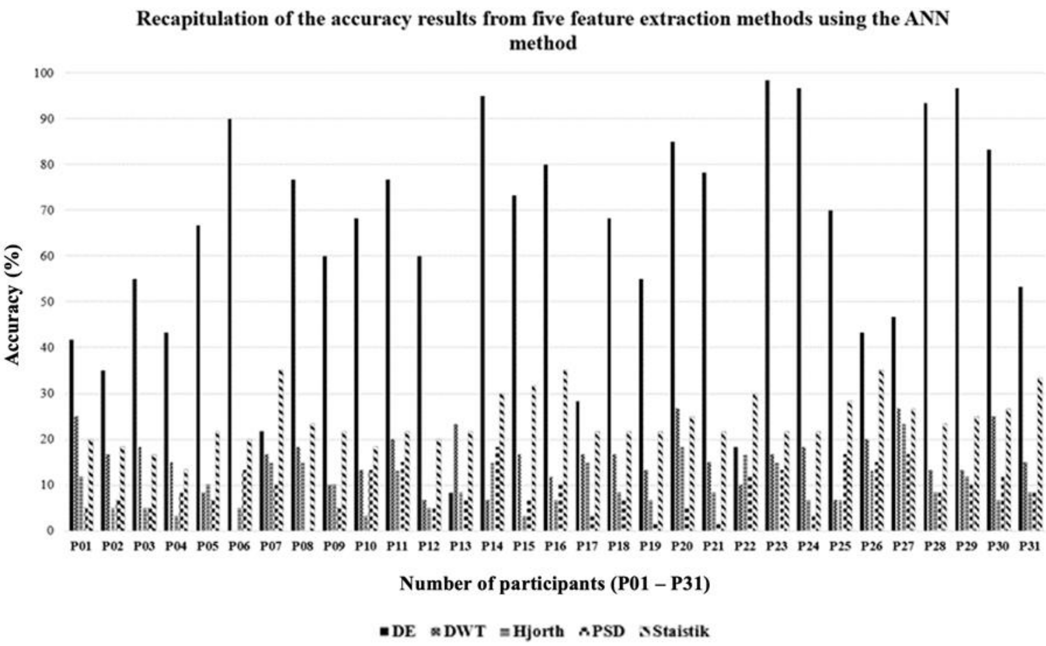

Figure 5. Visualization of the accuracy comparison of five feature extraction methods combined with the ANN method

For several subjects, such as P06, P13, P23, P24, P28, P29, and P31, the accuracy even exceeded 90%, indicating that DE can capture the characteristics of EEG signals in a more representative manner. Meanwhile, other features such as DWT, Hjorth, PSD, and statistical features show relatively lower performance, with an average accuracy under 35%. This considerable performance gap suggests that ANN is more effective at optimizing the nonlinear feature representations of DE. In contrast, the other features are less capable of providing sufficiently discriminative information for the model.

Figure 6 illustrates the classification performance using the SVM model. Similar to the ANN results, the DE feature consistently achieved the highest accuracy, with average values between 45% and 65%. This indicates that although SVM can leverage DE as an informative feature, its generalization capability remains limited in modeling the complexity of EEG signal patterns. The findings confirm that DE surpasses DWT, Hjorth parameters, PSD, and statistical features in classifying six Balinese script classes based on EEG data. By providing a more informative representation of the probabilistic structure of EEG activity, DE proves more effective in capturing non-linear and non-stationary brain dynamics [23]. The consistent improvement in accuracy further validates previous research, emphasizing that DE is particularly well-suited for modeling complex EEG patterns, especially when integrated with deep learning models [13]. Thus, DE can be regarded as the primary feature extraction approach, while other methods may serve as complementary techniques in hybrid frameworks to improve robustness. These results align with prior studies reporting the superior discriminative power of DE compared to conventional methods [10], [24], [25]. Furthermore, experimental outcomes show that DE consistently yields the highest accuracy across both ANN and SVM classifiers. Although overall accuracy ranged between 45% and 65%, ANN demonstrated better performance than SVM, suggesting its greater effectiveness in capturing the non-linear characteristics of EEG signals.

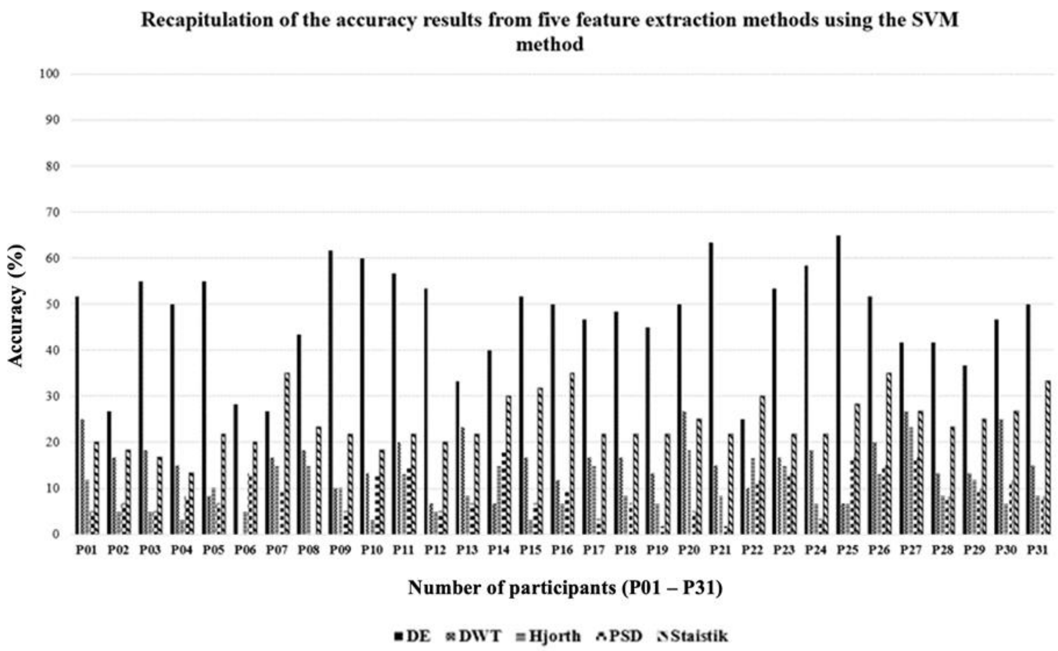

Figure 6. Visualization of the accuracy comparison of five feature extraction methods combined with the SVM method

Despite its advantages, classification performance still varies across participants. Addressing this challenge requires future studies to emphasize two key directions. First, data augmentation is essential, as the BISE dataset provides a limited number of samples per subject. Although the dataset meets the minimum threshold for sample size, techniques such as radius-synthetic minority over-sampling technique (Radius-SMOTE), adaptive synthetic sampling (ADASYN), and generative models (e.g., generative adversarial networks (GANs)) remain critical to improving generalization [26]. Second, advances in classification models are needed to better capture the spatial and temporal characteristics of EEG. Convolutional neural networks (CNNs) are effective for modeling spatial inter-channel dependencies, whereas recurrent neural network (RNN), long short-term memory (LSTM), and transformers provide stronger sequential modeling. Capsule networks also show promise in preserving hierarchical spatial information lost in conventional CNNs [13], [27]. Combining these architectures could lead to substantial performance gains.

In terms of real-world applications, EEG-based classification of Balinese script contributes to cultural heritage preservation. It enhances communication for individuals with disabilities, thereby reducing reliance on sign language. Additionally, this approach supports assistive technologies, adaptive learning, and rehabilitation, ultimately fostering greater accessibility for learners with communication or motor impairments. Integrating EEG-based recognition into educational settings also enables more inclusive and personalized learning experiences. However, current BCI hardware lacks specialized systems for detecting imagined speech, mainly because this process involves distributed activation across the frontal, temporal, parietal, and motor cortices [28].

4. CONCLUSION

Experimental results on the BISE dataset indicate that DE is the most effective feature extraction method for handling low-amplitude, non-stationary, and highly variable EEG signals. Compared with DWT, PSD, Hjorth, and statistical features, DE produces a superior representation because it reflects the complexity of the non-linear and non-stationary probabilistic distribution of EEG signals. This advantage allows DE to retain important information from the time and frequency domains, thereby improving classification accuracy, especially in recognizing the six Balinese scripts. However, other approaches require further study to improve the accuracy of Balinese script recognition, especially in terms of data augmentation and determining the optimal classification method that can effectively represent spatial and temporal information from EEG signal features. Further research is required to develop and integrate specialized hardware for speech imaging support assistive control, adaptive learning, rehabilitation, and improving accessibility for students with motor and communication disorders or disabilities.

FUNDING INFORMATION

This work is partially supported by Funding for the 2025 fiscal year, No. 503/UN48.16/PT/2025, from the Institute for Research and Community Service at the Universitas Pendidikan Ganesha.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
I Made Agus Wirawan	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ida Bagus Nyoman Pascima		✓	✓	✓	✓			✓		✓			✓	
Gede Surya Mahendra		✓	✓	✓	✓			✓		✓			✓	
I Made Candiasa					✓	✓	✓	✓		✓		✓	✓	
I Nyoman Sukajaya					✓	✓	✓	✓		✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The BISE dataset that supports the findings of this study is openly available in Mendeley Data at https://data.mendeley.com/datasets/c3m4s2dtcr/3.

REFERENCES

[1] C. Herff and T. Schultz, "Automatic speech recognition from neural signals: a focused review," *Frontiers in Neuroscience*, vol. 10, Sep. 2016, doi: 10.3389/fnins.2016.00429.

[2] L. Haji, O. M. Ahmad, S. R. M. Zeebaree, H. I. Dino, R. R. Zebari, and H. M. Shukur, "Impact of cloud computing and internet of things on the future internet," *Technology Reports of Kansai University*, vol. 62, no. 5, pp. 2179–2190, 2020.

[3] M. P. Branco *et al.*, "Brain-computer interfaces for communication: preferences of individuals with locked-in syndrome," *Neurorehabilitation and Neural Repair*, vol. 35, no. 3, pp. 267–279, Mar. 2021, doi: 10.1177/1545968321989331.

[4] S. Rasheed, "A review of the role of machine learning techniques towards brain–computer interface applications," *Machine Learning and Knowledge Extraction*, vol. 3, no. 4, pp. 835–862, Oct. 2021, doi: 10.3390/make3040042.

[5] X. Gu *et al.*, "EEG-based brain-computer interfaces (BCIs): a survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 18, no. 5, pp. 1645–1666, Sep. 2021, doi: 10.1109/TCBB.2021.3052811.

[6] L. A. Moctezuma, A. A. T.-García, L. V.-Pineda, and M. Carrillo, "Subjects identification using EEG-recorded imagined speech," *Expert Systems with Applications*, vol. 118, pp. 201–208, Mar. 2019, doi: 10.1016/j.eswa.2018.10.004.

[7] E. Canny, M. J. Vansteensel, S. M. A. van der Salm, G. R. M.-Putz, and J. Berezutskaya, “Boosting brain–computer interfaces with functional electrical stimulation: potential applications in people with locked-in syndrome,” *Journal of NeuroEngineering and Rehabilitation*, vol. 20, no. 1, Nov. 2023, doi: 10.1186/s12984-023-01272-y.
[8] D. R. Nayak, R. Dash, and B. Majhi, “Brain MR image classification using two-dimensional discrete wavelet transform and AdaBoost with random forests,” *Neurocomputing*, vol. 177, pp. 188–197, Feb. 2016, doi: 10.1016/j.neucom.2015.11.034.
[9] Z.-T. Liu, Q. Xie, M. Wu, W.-H. Cao, D.-Y. Li, and S.-H. Li, “Electroencephalogram emotion recognition based on empirical mode decomposition and optimal feature selection,” *IEEE Transactions on Cognitive and Developmental Systems*, vol. 11, no. 4, pp. 517–526, Dec. 2019, doi: 10.1109/TCDS.2018.2868121.
[10] D. L.-Bernal, D. Balderas, P. Ponce, and A. Molina, “A state-of-the-art review of EEG-based imagined speech decoding,” *Frontiers in Human Neuroscience*, vol. 16, Apr. 2022, doi: 10.3389/fnhum.2022.867281.
[11] S. Alzahrani, H. Banjar, and R. Mirza, “Systematic review of EEG-based imagined speech classification methods,” *Sensors*, vol. 24, no. 24, Dec. 2024, doi: 10.3390/s24248168.
[12] D. Parameshwaran and T. C. Thiagarajan, “High variability periods in the EEG distinguish cognitive brain states,” *Brain Sciences*, vol. 13, no. 11, Oct. 2023, doi: 10.3390/brainsci13111528.
[13] T. Ergin, M. A. Ozdemir, and A. Akan, “Emotion recognition with multi-channel EEG signals using visual stimulus,” in *2019 Medical Technologies Congress (TIPTEKNO)*, Oct. 2019, pp. 1–4, doi: 10.1109/TIPTEKNO.2019.8895242.
[14] M. A. Rahman, M. F. Hossain, M. Hossain, and R. Ahmmed, “Employing PCA and t-statistical approach for feature extraction and classification of emotion from multichannel EEG signal,” *Egyptian Informatics Journal*, vol. 21, no. 1, pp. 23–35, Mar. 2020, doi: 10.1016/j.eij.2019.10.002.
[15] H. Chao, L. Dong, Y. Liu, and B. Lu, “Emotion recognition from multiband EEG signals using CapsNet,” *Sensors*, vol. 19, no. 9, May 2019, doi: 10.3390/s19092212.
[16] I. M. A. Wirawan and K. Paramarta, “Acquisition of Balinese imagined spelling using electroencephalogram (BISE) dataset,” *Data in Brief*, vol. 60, Jun. 2025, doi: 10.1016/j.dib.2025.111454.
[17] A. M. Ismael, Ö. F. Alçin, K. H. Abdalla, and A. Şengür, “Two-stepped majority voting for efficient EEG-based emotion classification,” *Brain Informatics*, vol. 7, no. 1, Dec. 2020, doi: 10.1186/s40708-020-00111-3.
[18] S. Katsigiannis and N. Ramzan, “DREAMER: a database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices,” *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 1, pp. 98–107, Jan. 2018, doi: 10.1109/JBHI.2017.2688239.
[19] I. M. A. Wirawan, R. Wardoyo, D. Lelono, and S. Kusrohmaniah, “Modified weighted mean filter to improve the baseline reduction approach for emotion recognition,” *Emerging Science Journal*, vol. 6, no. 6, pp. 1255–1273, Sep. 2022, doi: 10.28991/ESJ-2022-06-06-03.
[20] Y. Yang, Q. Wu, Y. Fu, and X. Chen, “Continuous convolutional neural network with 3D input for EEG-based emotion recognition,” in *Neural Information Processing (ICONIP 2018)*, Springer, Cham, 2018, pp. 433–443, doi: 10.1007/978-3-030-04239-4_39.
[21] J. A. M.-Correa, M. K. Abadi, N. Sebe, and I. Patras, “AMIGOS: a dataset for affect, personality and mood research on individuals and groups,” *IEEE Transactions on Affective Computing*, vol. 12, no. 2, pp. 479–493, Apr. 2021, doi: 10.1109/TAFFC.2018.2884461.
[22] O. Faust, U. R. Acharya, H. Adeli, and A. Adeli, “Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis,” *Seizure*, vol. 26, pp. 56–64, Mar. 2015, doi: 10.1016/j.seizure.2015.01.012.
[23] I. M. A. Wirawan, R. Wardoyo, D. Lelono, S. Kusrohmaniah, and S. Asrori, “Comparison of baseline reduction methods for emotion recognition based on electroencephalogram signals,” in *2021 Sixth International Conference on Informatics and Computing (ICIC)*, 2021, pp. 1–7, doi: 10.1109/ICIC54025.2021.9632948.
[24] Y. Dai, X. Wang, P. Zhang, W. Zhang, and J. Chen, “Sparsity constrained differential evolution enabled feature-channel-sample hybrid selection for daily-life EEG emotion recognition,” *Multimedia Tools and Applications*, vol. 77, no. 17, pp. 21967–21994, Sep. 2018, doi: 10.1007/s11042-018-5618-0.
[25] Y. Lu, X. Yao, W. Wang, L. Zhou, and T. Wu, “Emotion recognition classification with differential entropy and power spectral density features,” in *Proceedings of International Conference on Image, Vision and Intelligent Systems 2023 (ICIVIS 2023)*, 2024, pp. 541–548, doi: 10.1007/978-981-97-0855-0_51.
[26] B. G.-Martinez, A. M.-Rodrigo, R. Alcaraz, and A. F.-Caballero, “A review on nonlinear methods using electroencephalographic recordings for emotion recognition,” *IEEE Transactions on Affective Computing*, vol. 12, no. 3, pp. 801–820, Jul. 2021, doi: 10.1109/TAFFC.2018.2890636.
[27] C. Sun, A. Shrivastava, S. Singh, and A. Gupta, “Revisiting unreasonable effectiveness of data in deep learning era,” in *2017 IEEE International Conference on Computer Vision (ICCV)*, Oct. 2017, pp. 843–852, doi: 10.1109/ICCV.2017.97.
[28] I. M. A. Wirawan, K. Y. E. Aryanto, I. N. Sukajaya, N. N. M. Agustini, and D. A. W. M. Putri, “Hybrid method for optimizing emotion recognition models on electroencephalogram signals,” *IAES International Journal of Artificial Intelligence*, vol. 14, no. 3, pp. 2302–2314, Jun. 2025, doi: 10.11591/ijai.v14.i3.pp2302-2314.

BIOGRAPHIES OF AUTHORS

I Made Agus Wirawan is an associate professor in the Master of Computer Science Study Program at Universitas Pendidikan Ganesha, Bali, Indonesia. He earned bachelor's, master's, and doctorate degrees in the Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences, Universitas Gajah Mada, Yogyakarta, Indonesia. His areas of research interest include machine learning, artificial intelligence, and deep learning. He can be contacted at email: imade.aguswirawan@undiksha.ac.id.

Ida Bagus Nyoman Pascima is a lecturer in the Department of Informatics Engineering, Faculty of Engineering and Vocational Studies, Universitas Pendidikan Ganesha, Bali, Indonesia. His areas of research interest include machine learning, artificial intelligence, and deep learning. He can be contacted at email: gus.pascima@undiksha.ac.id.

Gede Surya Mahendra is a lecturer in the Department of Informatics Engineering, Faculty of Engineering and Vocational Studies, Universitas Pendidikan Ganesha, Bali, Indonesia. His areas of research interest include machine learning, artificial intelligence, and decision support systems. He can be contacted at email: gmahendra@undiksha.ac.id.

I Made Candiasa is a professor in the Department of Mathematics at Universitas Pendidikan Ganesha, Bali, Indonesia, with primary expertise in mathematics education and educational technology. He earned his Ph.D. in Educational Technology from Universitas Negeri Jakarta (UNJ) in 2003. His research topics include the development of quantitative analysis methods based on data mining. He can be contacted at email: candiasa@undiksha.ac.id.

I Nyoman Sukajaya is an associate professor in the Department of Mathematics, Universitas Pendidikan Ganesha. He achieved a Ph.D. degree at the Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember (ITS) in 2017, and his master's degree was completed in 1999 at the Department of Informatics Engineering, Institut Teknologi Bandung. His research topics are data mining, student profiling, and serious games in education. He is also a reviewer for some qualified international journals. He can be contacted at email: nyoman.sukajaya@undiksha.ac.id.