

Natural and Horizontal Visibility Graphs of EEG Power Spectra for Autism Spectrum Disorder Classification

Muhammad Saifullah Nur¹, Melinda Melinda¹, Yuwaldi Away¹, Siti Rusdiana², Souvik Das³, Zulfan Zulfan⁴

¹ Department of Electrical and Computer Engineering, Faculty of Engineering, Universitas Syiah Kuala, Banda Aceh, Indonesia

² Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia

³ Department of Industrial Design, National Institute of Technology Rourkela, Rourkela, India

⁴ Department of Informatics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Indonesia

Corresponding author: Melinda Melinda (e-mail: melinda@usk.ac.id), **Author(s) Email:** Muhammad Saifullah Nur (e-mail: msaifullah@mhs.usk.ac.id), Yuwaldi Away (e-mail: yuwaldi@usk.ac.id), Siti Rusdiana (e-mail: siti.rusdiana@usk.ac.id), Souvik Das (e-mail: rndas9@gmail.com), Zulfan Zulfan (e-mail: zulfan.abdullah@usk.ac.id)

Abstract Autism spectrum disorder (ASD) is primarily identified through behavioral and developmental assessment, which may require specialist expertise and considerable time. Electroencephalography (EEG) offers non-invasive neurophysiological information, but reliable ASD classification remains challenging because EEG signals are nonstationary and highly variable across individuals. This study evaluates whether visibility-graph topology derived from EEG power spectral density (PSD) curves provides complementary information beyond conventional spectral descriptors. Resting-state EEG from the Banda Aceh dataset (7 ASD and 7 typically developing participants, 250 Hz) and the KAU dataset (8 ASD and 8 control participants, 256 Hz) were processed independently. Preprocessing included quality inspection, 0.5–45-Hz zero-phase filtering, dataset-specific 50/60-Hz notch filtering, common average referencing, and non-overlapping 30-s segmentation. Welch PSD was estimated using 2-s Hann windows with 50% overlap across five frequency bands. Direct PSD, natural visibility graph features, and horizontal visibility graph features were compared using RBF-SVM and a six-hidden-layer MLP. Evaluation used subject-wise balanced cross-validation, with performance calculated at the epoch level from participant-disjoint outer-test folds. VG-NVG-PSD with SVM achieved the best observed accuracy of $97.14 \pm 3.29\%$ on Banda Aceh, representing a 0.97-percentage-point numerical gain over direct PSD-SVM. VG-HVG-PSD with SVM achieved $96.83 \pm 2.34\%$ on KAU, representing a 0.35-percentage-point gain. SVM produced the highest observed configuration on both datasets, whereas graph-spectral transformation did not consistently improve MLP performance. Bonferroni-corrected pairwise comparisons did not establish statistical superiority among individual methods. These findings indicate that PSD-derived visibility graphs provide an interpretable complementary representation for EEG-based ASD classification, although the preferred visibility criterion was dataset-dependent. Larger cohorts and external validation are required before clinical generalization.

Keywords Autism spectrum disorder; Electroencephalography; Power spectral density; Visibility graph; Support vector machine

1. Introduction

Autism spectrum disorder (ASD) is a heterogeneous neurodevelopmental condition characterized by persistent differences in social communication and interaction together with restricted or repetitive behaviors, interests, or activities [1]. Its manifestations vary considerably across individuals in cognitive ability, language, sensory processing, and required support [2]. Recent surveillance and global prevalence studies confirm that ASD remains an important developmental health concern [3], [4]. Clinical identification primarily relies on developmental history, behavioral observation,

caregiver interviews, and standardized instruments [1], [2]. Although essential, comprehensive assessment may require specialist expertise and considerable time, motivating research into complementary neurophysiological approaches such as electroencephalography (EEG) [5]. EEG-based ASD studies have investigated spectral power, functional connectivity, nonlinear characteristics, and machine-learning representations [6]. Resting-state studies have reported ASD-related spectral and connectivity differences [7], while meta-analytic evidence indicates alterations across several frequency bands [8]. Reliable

classification nevertheless remains challenging because EEG is nonstationary, noise-sensitive, multichannel, and highly variable across individuals. Small independent cohorts also increase the risk of overfitting, particularly when high-dimensional representations or complex models are used [9], [10].

Recent approaches illustrate the rapid development of EEG-based ASD classification. Hybrid lightweight deep features combined with SVM achieved 96.44% accuracy [11], sparse feature mapping with pretrained convolutional networks reported 98.88% [12], and a spectrogram-based deep-learning approach achieved 99.15% [13]. More recently, TFSNet reported average accuracies of 98.68% and 97.14% on two EEG datasets [14]. However, these studies employed different datasets, preprocessing procedures, feature spaces, model architectures, and validation protocols. Their numerical accuracies therefore do not directly establish whether one EEG representation provides more discriminatory information than another under matched experimental conditions. Power spectral density (PSD) remains attractive because it provides an interpretable representation of EEG power across conventional frequency bands [7], [8]. Conventional PSD descriptors, however, mainly summarize spectral magnitude and distribution and do not explicitly capture the geometric organization of the PSD curve. Visibility graph analysis transforms ordered samples into graph nodes connected according to geometric visibility. Visibility-graph representations have been applied to EEG classification [15], while horizontal visibility graphs have demonstrated discriminative capability in EEG recognition tasks [16]. Reviews further describe visibility graphs as a bridge between ordered-signal analysis and complex-network topology [17]. Natural visibility graphs (NVG) preserve local and longer-range geometric relationships, whereas horizontal visibility graphs (HVG) apply a stricter criterion and generally produce sparser topologies [15], [16], [17]. Their relative value when derived from identical EEG spectral representations therefore requires controlled evaluation.

Validation design is equally important because each participant contributes multiple EEG epochs. Random epoch-level partitioning may place epochs from the same participant in both training and testing sets, allowing participant-specific information to influence the reported performance [18], [19]. Consequently, participant identity should determine train-test membership when evaluating generalization to previously unseen individuals, even when individual epochs remain the classifier inputs and prediction units. The Banda Aceh EEG dataset has been established for ASD-related analysis [20], while the KAU dataset has been evaluated using Fisher linear discriminant analysis [21] and SWT-based FLDA [22]. Related studies have also investigated decomposition-based EEG feature extraction for ASD classification [23]. However, these studies did not directly compare conventional PSD descriptors with NVG- and HVG-derived topology generated from the same PSD curves using identical preprocessing, classifiers, and participant-disjoint outer testing. The research gap is therefore not simply the absence of high-performing EEG-ASD classifiers, but the limited evidence on whether PSD-

curve topology provides complementary discriminatory information beyond conventional spectral descriptors under controlled conditions. It also remains unclear whether NVG and HVG behave consistently across EEG datasets with different acquisition characteristics.

This study addresses these gaps by directly comparing PSD, VG-NVG-PSD, and VG-HVG-PSD representations using RBF-SVM and a six-hidden-layer MLP. The contributions are: (1) direct comparison of conventional PSD descriptors with NVG- and HVG-derived topology from identical PSD curves; (2) consistent preprocessing, frequency-band definitions, graph measures, classifiers, and evaluation settings; (3) independent evaluation on the Banda Aceh and KAU datasets; and (4) subject-wise balanced cross-validation in which participant identity determines outer-fold membership and all epochs from each held-out participant remain exclusively in the test set. The objective is to determine whether PSD-derived visibility-graph features provide complementary information for epoch-level ASD classification from unseen participants and whether the preferred visibility criterion is consistent across datasets. The remainder of this paper is organized as follows. Section 2 describes the datasets, preprocessing, feature extraction, classification, validation, and statistical analysis. Section 3 presents the results, Section 4 discusses the findings and limitations, and Section 5 concludes the study.

II. Materials and Method

This study compared three EEG feature representations: conventional power spectral density (PSD), natural visibility graph features derived from PSD (VG-NVG-PSD), and horizontal visibility graph features derived from PSD (VG-HVG-PSD). Each representation was evaluated using an RBF-SVM and an MLP, yielding six feature-classifier configurations per dataset. The Banda Aceh and KAU datasets were analyzed independently because of differences in acquisition characteristics. The overall workflow is illustrated in Fig. 1. Individual 30-s epochs were used as classifier inputs and prediction units, whereas participant identity determined train-validation-test membership.

A. Dataset

The KAU EEG data were obtained from King Abdulaziz University, Jeddah, Saudi Arabia [21], [22]. The subset evaluated in this study contained 16 participant recording units, comprising 8 ASD and 8 control participants. The ASD group included five males and three females aged 6–20 years, with an aggregate recording duration of 4,104.2 s. The control group consisted of eight males aged 9–13 years, with an aggregate recording duration of 4,534.9 s. EEG signals were recorded under resting conditions using Ag/AgCl electrodes, a g.tec acquisition system, a USB amplifier, and BCI2000 software [21], [22]. The sampling frequency was 256 Hz. Sixteen retained EEG channels were Fp1, F3, F7, T3, T5, O1, C4, Fp2, Fz, F4, F8, C3, Cz, Pz, Oz, and O2. ASD and control labels were retained from the provided dataset documentation. The Banda Aceh dataset analyzed in this study included 14 participants: 7 with ASD and 7 typically developing (TD). Approximately 15 min of eyes-closed resting-state

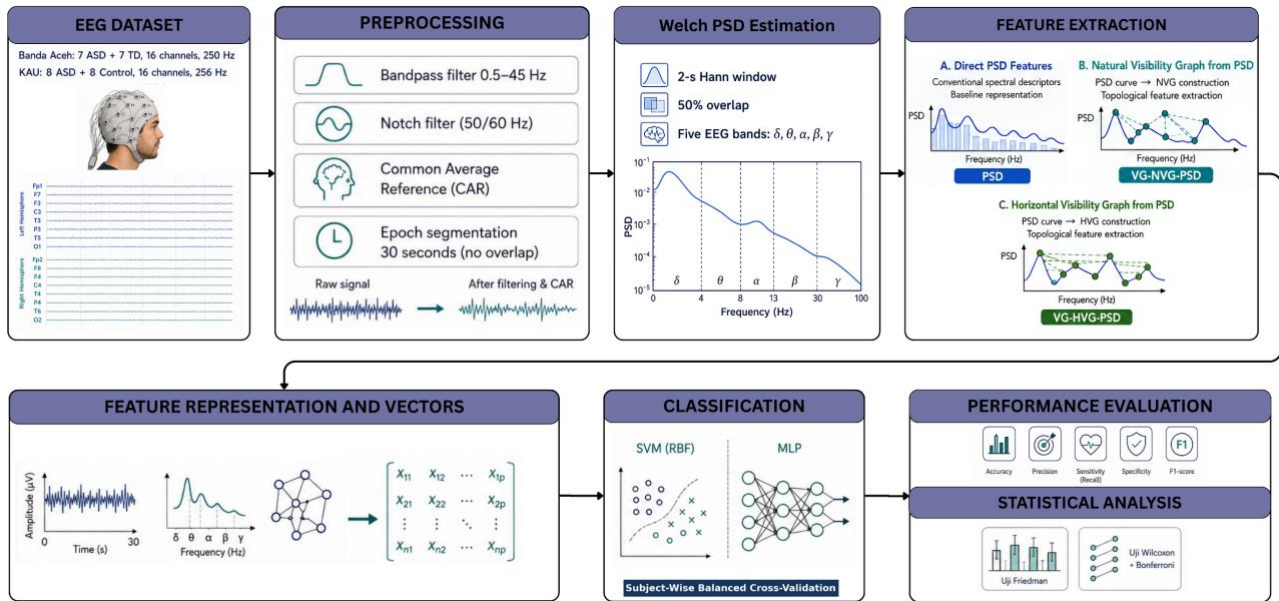


Fig. 1. Proposed graph-spectral EEG classification framework incorporating preprocessing, PSD estimation, visibility-graph feature extraction, classification, participant-disjoint outer testing, internal validation, and statistical analysis.

EEG was recorded from each participant at 250 Hz using an OpenBCI Cyton Biosensing Board, EEG cap, electrode gel, OpenBCI USB interface, and associated acquisition software [20], [24]. The 16 recorded channels were Fp1, Fp2, F3, F4, F7, F8, C3, C4, T3, T4, T5, T6, P3, P4, O1, and O2. Recordings were conducted under controlled resting conditions to reduce external distraction. Anonymous participant identifiers were retained throughout preprocessing, feature extraction, and validation. Ethical approval for the Banda Aceh data collection was granted by the Health Research Ethics Committee under approval No. 117/EA/FK/2024 [20]. The present analysis used previously collected EEG recordings and involved no additional participant recruitment.

B. EEG Preprocessing

Each EEG recording was processed independently while preserving its dataset identifier, participant identifier, and class label. Initial quality inspection verified file readability, expected channel number and order, signal dimensions, non-finite values, and channels showing no amplitude variation. The same preprocessing sequence was applied consistently to both datasets [25], [26]. A fifth-order zero-phase Butterworth high-pass filter with a cutoff frequency of 0.5 Hz was first applied to reduce slow baseline drift. Dataset-specific notch filtering was then performed at 50 Hz for Banda Aceh and 60 Hz for KAU to suppress power-line interference. The recordings were subsequently re-referenced using a common average reference across the 16 retained channels and filtered using a fifth-order zero-phase Butterworth low-pass filter with a cutoff frequency of 45 Hz. Automated independent component analysis and bad-channel interpolation were not applied because equivalent artifact annotations and channel-quality metadata were not consistently available for both datasets. Applying different artifact-correction procedures between datasets could introduce an additional

preprocessing difference into the controlled representation comparison. This limitation is discussed in Section 4. The filtered EEG signals were segmented into non-overlapping 30-s epochs. Each Banda Aceh epoch contained 7,500 samples per channel, whereas each KAU epoch contained 7,680 samples per channel. Final segments shorter than 30 s were discarded. Each retained epoch inherited the participant identifier and diagnostic label of its source recording. Feature standardization was performed only within the cross-validation procedure to prevent information leakage.

C. Spectral and Graph-Spectral Feature Extraction

1. Welch PSD Estimation

PSD was estimated independently for every 30-s epoch and EEG channel using Welch's averaged-periodogram method [27]. Each epoch was divided into 2-s segments using a Hann window with 50% overlap. The segment lengths were 500 samples for Banda Aceh and 512 samples for KAU, yielding the same frequency resolution of 0.5 Hz.

The Welch PSD estimate is defined in Eq. (1):

$$\hat{p}_{xx}(f) = \frac{1}{K} \sum_{r=0}^{K-1} \frac{1}{f_s L U} \left| \sum_{n=0}^{L-1} w[n] x_r[n] e^{-j2\pi f n / f_s} \right|^2 \quad (1)$$

where $\hat{p}_{xx}(f)$ is the estimated PSD at frequency f , K is the number of overlapping segments, L is the segment length, $w[n]$ is the Hann window, f_s is the sampling frequency, and U is the window-power normalization factor [27]. The normalization factor used in Eq. (1) is defined in Eq. (2):

$$U = \frac{1}{L} \sum_{n=0}^{L-1} w^2[n] \quad (2)$$

The estimated PSD was restricted to 0.5–45 Hz and divided into delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–45 Hz) bands [8], [26]. To avoid duplicate boundary bins, the first four intervals were lower-inclusive and upper-exclusive, whereas the gamma interval included 45 Hz. At 0.5-Hz resolution, the respective bands contained 7, 8, 10, 34, and 31 spectral samples. These samples subsequently constituted the nodes used for visibility-graph construction.

2. Direct PSD Features

Direct PSD served as the conventional spectral baseline. Ten descriptors were extracted from every EEG channel and frequency band: mean power, median power, total spectral power, peak frequency, peak power, 95% spectral edge frequency, band-power ratio, skewness, kurtosis, and spectral entropy. For a frequency band b containing N_b PSD values $P_{b,m}$, mean power was calculated using Eq. (3):

$$\mu_b = \frac{1}{N_b} \sum_{m=1}^{N_b} P_{b,m} \quad (3)$$

Median spectral power was obtained using Eq. (4):

$$\tilde{P}_b = \text{median}(P_{b,1}, P_{b,2}, \dots, P_{b,N_b}) \quad (4)$$

The implemented total spectral-power descriptor was calculated as the discrete sum shown in Eq. (5):

$$S_b = \sum_{m=1}^{N_b} P_{b,m} \quad (5)$$

Because all PSD estimates used the same 0.5-Hz frequency spacing, the discrete quantity in Eq. (5) is proportional to frequency-integrated band power through the constant factor $\Delta f = 0.5$ Hz. Peak frequency and peak power were obtained from the maximum PSD value within each band. The location of the maximum was determined using Eq. (6):

$$m_b^* = \arg \max_m P_{b,m}, f_b^{\text{peak}} = f_{b,m_b^*}, P_b^{\text{peak}} = P_{b,m_b^*} \quad (6)$$

The 95% spectral edge frequency was calculated using Eq. (7):

$$f_{\text{SEF}95,b} = \min \left\{ f_{b,q} : \frac{\sum_{m=1}^q P_{b,m}}{\sum_{m=1}^{N_b} P_{b,m}} \geq 0.95 \right\} \quad (7)$$

To represent the contribution of each frequency band relative to the analyzed spectrum, the band-power ratio was calculated using Eq. (8):

$$R_b = \frac{S_b}{\sum_{b' \in B} S_{b'}}, B = \{\delta, \theta, \alpha, \beta, \gamma\} \quad (8)$$

For spectral entropy, each PSD value was first normalized according to Eq. (9):

$$q_{b,m} = \frac{P_{b,m}}{S_b} \quad (9)$$

The normalized probabilities from Eq. (9) were then used to calculate spectral entropy using Eq. (10):

$$H_b^{\text{PSD}} = - \sum_{m=1}^{N_b} q_{b,m} \log_2 q_{b,m} \quad (10)$$

Terms with $q_{b,m} = 0$ were treated as zero in the entropy summation. Skewness and kurtosis were additionally calculated using bias-corrected sample estimates. With 16 channels, five frequency bands, and ten descriptors, the direct PSD representation contained $16 \times 5 \times 10 = 800$ features per epoch. This feature definition is consistent with the implemented extraction pipeline.

3. Visibility Graph Construction

For graph-spectral extraction, the ordered PSD samples within each EEG channel and frequency band were treated as frequency–power pairs. Each PSD sample represented one graph node. Independent undirected and unweighted graphs were constructed for every channel–band combination, with no connections formed across different channels or frequency bands. Let f_i and p_i denote the frequency and PSD value associated with node i . For an NVG, nodes i and j , where $i < j$, were connected when every intermediate node k satisfied the natural visibility condition defined in Eq. (11) [15], [17], [28]:

$$p_k < p_i + (p_j - p_i) \frac{f_k - f_i}{f_j - f_i}, i < k < j \quad (11)$$

The condition in Eq. (11) requires all intermediate spectral points to lie below the straight line connecting the two endpoint nodes. For an HVG, the more restrictive horizontal visibility condition was applied using Eq. (12) [16], [17], [29]:

$$p_k < \min(p_i, p_j), i < k < j \quad (12)$$

Because Eq. (12) is stricter, HVG generally produces a sparser topology than NVG and emphasizes relative ordering and local spectral structure. Both graph types were generated from identical PSD curves, so differences between VG-NVG-PSD and VG-HVG-PSD arose only from the visibility criterion.

4. Topological Graph Features

Each NVG and HVG was summarized using eight predefined graph measures: average degree, maximum degree, density, radius, diameter, degree entropy, global efficiency, and clique number [15], [17], [30]. For a graph represented by adjacency matrix A , the degree of node i was calculated using Eq. (13):

$$k_i = \sum_{j=1}^N A_{ij} \quad (13)$$

The node degrees from Eq. (13) were averaged according to Eq. (14):

$$\bar{k} = \frac{1}{N} \sum_{i=1}^N k_i \quad (14)$$

Graph density was determined from the number of edges using Eq. (15):

$$D = \frac{2 |E|}{N(N-1)} \quad (15)$$

where N denotes the number of graph nodes and $|E|$ denotes the number of edges. To quantify the heterogeneity of the graph degree distribution, $p(d) = n_d/N$ was defined as the proportion of nodes having degree d . Degree entropy was then calculated using Eq. (16):

$$H_{\text{deg}} = - \sum_d p(d) \log_2 p(d) \quad (16)$$

Global efficiency was calculated from the shortest-path distances d_{ij} according to Eq. (17):

$$E_{\text{glob}} = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \quad (17)$$

The remaining graph measures were defined collectively in Eq. (18):

$$k_{\text{max}} = \max_i k_i, r(G) = \min_i r_i, d(G) = \max_i d_i, \omega(G) = \max_{C \in \mathcal{C}(G)} |C| \quad (18)$$

where e_i denotes node eccentricity and $\mathcal{C}(G)$ denotes the set of cliques in graph G . These measures were interpreted as within-band topological summaries. This consideration is particularly relevant for delta, theta, and alpha because their PSD curves contain fewer nodes than beta and gamma. The graph metrics were therefore used to characterize the topology of each band-specific PSD curve rather than to compare graph size directly across bands. Eight measures were extracted from 16 EEG channels and five bands, yielding $16 \times 5 \times 8 = 640$ features for both VG-NVG-PSD and VG-HVG-PSD. The PSD, VG-NVG-PSD, and VG-HVG-PSD representations were evaluated separately and were not concatenated. Because direct PSD contained 800 features whereas the graph representations contained 640 features, performance differences were interpreted as representation-level differences rather than effects attributable exclusively to graph topology

D. Classification Models

Before classifier fitting, every feature dimension was standardized using statistics estimated only from the model-training subset. The z-score transformation is given in Eq. (19):

$$z_{ij} = \frac{x_{ij} - \mu_j^{\text{train}}}{\sigma_j^{\text{train}}} \quad (19)$$

The training means and standard deviations in Eq. (19) were subsequently applied unchanged to internal-validation and outer-test data.

1. Support Vector Machine

The SVM received one standardized feature vector for each EEG epoch. Nonlinear similarity was modeled using the RBF kernel defined in Eq. (20) [31]:

$$K(x, x') = \exp(-\gamma \|x - x'\|^2) \quad (20)$$

Using the kernel in Eq. (20), the SVM decision function was expressed in Eq. (21):

$$g(x) = \sum_{i=1}^{N_{\text{SV}}} \alpha_i y_i K(x_i, x) + b \quad (21)$$

where N_{SV} is the number of support vectors, α_i is the learned coefficient, $y_i \in \{-1, +1\}$ is the class label, and b is the intercept. The SVM used $C = 1.0$, $\gamma = \text{scale}$, balanced class weighting, and probability estimation. ASD was treated as the positive class, and estimated probabilities were converted to epoch-level labels using a fixed threshold of 0.5. Identical SVM settings were maintained across datasets and feature representations.

2. Multilayer Perceptron

The MLP received the same standardized feature vectors used by the SVM. It comprised six fully connected hidden layers containing 64 neurons each with ReLU activation [32]. The transformation at hidden layer ℓ is defined in Eq. (22):

$$h^{(\ell)} = \text{ReLU}(W^{(\ell)} h^{(\ell-1)} + b^{(\ell)}) \quad (22)$$

The final hidden representation was converted into an ASD probability through the sigmoid output defined in Eq. (23):

$$\hat{p} = \frac{1}{1 + \exp[-(w_o^T h^{(6)} + b_o)]} \quad (23)$$

The MLP was optimized using binary cross-entropy and Adam with an initial learning rate of 0.001. Training was limited to 50 epochs with a batch size of 128. Early stopping monitored internal-validation loss with a patience of 20 epochs and restored the model weights corresponding to the minimum validation loss. The learning rate was reduced by a factor of 0.5 when validation loss stopped improving, with a minimum value of 1×10^{-6} . Gradient clipping used a maximum norm of 1.0, and class weights were calculated exclusively from model-training data. The architecture was intentionally kept identical across representations and datasets so that differences in performance reflected the evaluated feature-classifier combinations rather than changes in network structure.

E. Subject-Wise Balanced Cross-Validation

Subject-wise balanced cross-validation was used to evaluate classification of epochs originating from participants excluded from model development [18], [19], [33], [34]. Although individual 30-s epochs constituted the classifier inputs and prediction units, participant identity exclusively determined the cross-validation partitions. Banda Aceh was evaluated using seven outer folds. In every fold, one ASD participant and one TD participant were held out for testing, while the remaining 12 participants formed the outer-training pool. KAU was evaluated using eight outer folds, each holding out one ASD and one control participant and leaving 14 participants in the outer-training pool. Each participant appeared in the outer-test partition exactly once. The same held-out participant pairs were used across all six feature-classifier configurations within each dataset. Internal validation was restricted to participants in the corresponding outer-training pool. One participant from each class was assigned to internal validation, and all epochs from these participants were excluded from model

fitting. The remaining outer-training participants constituted the model-training subset. Consequently, participant identity remained mutually exclusive among training, internal validation, and outer testing. Feature scaling was fitted exclusively on model-training epochs. Internal-validation participants were used only for MLP early stopping and learning-rate adjustment. Outer-test participants did not contribute to scaling, validation, classifier fitting, or model adjustment. Accordingly, the reported metrics represent **epoch-level classification under participant-disjoint outer testing**. They do not

Algorithm 1. Participant-disjoint graph-spectral EEG classification and evaluation procedure.

Input: EEG recordings, participant IDs, class labels, PSD/NVG/HVG definitions, SVM, and MLP

Output: Fold-level and cross-fold epoch-level performance metrics

```

1: for each dataset independently do
2:   verify recordings, channels, participant IDs, and labels
3:   apply high-pass, notch, CAR, and low-pass preprocessing
4:   segment recordings into non-overlapping 30-s epochs
5:   for each epoch and EEG channel do
6:     estimate Welch PSD
7:     extract ten direct PSD descriptors
8:     construct within-band NVG and HVG
9:     extract eight graph-topological measures
10:  end for
11:  construct balanced outer folds using participant identity
12:  for each outer fold do
13:    hold out one ASD and one TD/control participant for testing
14:    select participant-disjoint internal-validation participants
15:    use the remaining participants for model training
16:    fit standardization using model-training epochs only
17:    apply the fitted transformation to validation and test epochs
18:    train SVM or MLP
19:    use internal validation only for MLP training control
20:    predict epochs belonging to held-out participants
21:    calculate the five performance metrics
22:  end for
23:  summarize metrics across outer folds
24:  perform the Friedman omnibus test
25:  if the corresponding Friedman test is significant then
26:    perform two-sided Wilcoxon signed-rank comparisons
27:    apply Bonferroni correction across 15 comparisons
28:  end if
29: end for
    
```

represent random epoch-level cross-validation or one aggregated diagnostic decision per participant. The complete procedure is summarized in [Algorithm 1](#).

F. Performance Evaluation and Statistical Analysis

ASD was considered the positive class and TD/control the negative class. Let TP and TN denote correctly classified positive and negative epochs, while FP and FN denote the corresponding misclassifications.

Accuracy was calculated using [Eq. \(24\)](#):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (24)$$

Precision was calculated using [Eq. \(25\)](#):

$$\text{Precision} = \frac{TP}{TP + FP} \quad (25)$$

Sensitivity was calculated using [Eq. \(26\)](#):

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (26)$$

Specificity was calculated using [Eq. \(27\)](#):

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (27)$$

F1-score was calculated using [Eq. \(28\)](#):

$$F_1 = \frac{2TP}{2TP + FP + FN} \quad (28)$$

The five metrics defined in [Eqs. \(24\)–\(28\)](#) were calculated independently for each participant-separated outer fold and summarized as mean $\pm$ standard deviation across seven Banda Aceh folds and eight KAU folds [\[35\]](#). Statistical comparison was performed independently for the two datasets. Because the six feature–classifier configurations were evaluated using identical held-out participant pairs, their fold-level scores were treated as related observations. For $k = 6$ methods evaluated over N outer folds, the Friedman statistic was calculated using [Eq. \(29\)](#) [\[35\]](#):

$$\chi_F^2 = \frac{12}{Nk(k+1)} \sum_{j=1}^k R_j^2 - 3N(k+1) \quad (29)$$

where R_j denotes the sum of ranks assigned to method j across the outer folds. The Friedman test was applied separately to accuracy, precision, sensitivity, specificity, and F1-score using $\alpha = 0.05$, with standard correction for tied ranks when required. When a Friedman test was significant, two-sided Wilcoxon signed-rank tests were performed on the paired fold-level scores for the corresponding metric. With six methods, the number of pairwise comparisons was calculated using [Eq. \(30\)](#):

$$M = \binom{6}{2} = \frac{6(6-1)}{2} = 15 \quad (30)$$

Accordingly, the Bonferroni-adjusted significance threshold was calculated using [Eq. \(31\)](#):

$$\alpha_{\text{Bonf}} = \frac{0.05}{15} = 0.00333 \quad (31)$$

Pairwise differences were considered statistically significant only when the Wilcoxon p -value was below the threshold defined in [Eq. \(31\)](#). Differences that did not

satisfy this criterion were interpreted as numerical or observed performance differences rather than evidence of statistical superiority.

III. Results

A. Preprocessing Output and Experimental Summary

Preprocessing produced 417 non-overlapping 30-s epochs from the Banda Aceh dataset, comprising 207 ASD and 210 typically developing (TD) epochs. The KAU dataset produced 282 epochs, comprising 133 ASD and 149 control epochs. Individual epochs were used for feature extraction, classification, and performance calculation, whereas participant identity exclusively determined outer-fold membership. Consequently, all epochs from each held-out participant remained in the corresponding outer-test fold and were not used during model development. Banda Aceh was evaluated using seven subject-wise balanced outer folds, with one ASD and one TD participant held out in each fold. KAU was evaluated using eight outer folds, with one ASD and one control participant held out per fold. The same held-out participant pairs were used across all six feature-classifier configurations within each dataset.

B. Classification Performance

The epoch-level classification performance obtained under participant-disjoint outer testing is presented in Table 1. Values are reported as mean $\pm$ standard deviation across the seven Banda Aceh folds and eight KAU folds. Bold values indicate the highest observed value for each metric within the corresponding dataset. On Banda Aceh, VG-NVG-PSD-SVM produced the best observed accuracy of $97.14 \pm 3.29\%$ and F1-score of $96.95 \pm 3.59\%$. The same configuration achieved precision and specificity of 100.00%, whereas PSD-MLP produced the highest observed sensitivity of $96.17 \pm 3.00\%$. Compared with PSD-SVM, VG-NVG-PSD-SVM increased accuracy numerically by 0.97 percentage points, from 96.17% to 97.14%, and F1-score by 1.03 percentage points. Its accuracy variability was also slightly lower (SD = 3.29%) than that of PSD-SVM (SD =

3.68%). In contrast, VG-HVG-PSD performed substantially worse on Banda Aceh, reaching $87.28 \pm 4.51\%$ accuracy with SVM and $84.64 \pm 5.36\%$ with MLP. On KAU, VG-HVG-PSD-SVM achieved the best observed accuracy of $96.83 \pm 2.34\%$, sensitivity of $95.54 \pm 5.23\%$, and F1-score of $96.56 \pm 2.56\%$. PSD-SVM achieved the highest precision and specificity, both at 100.00%, but showed lower sensitivity at $92.56 \pm 8.23\%$. Relative to PSD-SVM, VG-HVG-PSD-SVM provided a 0.35-percentage-point numerical increase in accuracy and a 2.98-percentage-point increase in sensitivity. Its accuracy standard deviation also decreased from 3.88% to 2.34%. These results indicate that the preferred visibility criterion was dataset-dependent: NVG produced the highest observed performance on Banda Aceh, whereas HVG was more effective on KAU. Graph transformation therefore did not provide a uniform improvement across datasets or classifiers.

C. Statistical Analysis

The statistical comparison of the six feature-classifier configurations was performed using paired outer-fold results because all methods were evaluated using identical held-out participant pairs. The Friedman omnibus results are presented in Table 2. For Banda Aceh, significant omnibus differences were observed for accuracy ($p = 0.00025$), precision ($p = 0.01745$), specificity ($p = 0.02212$), and F1-score ($p = 0.00144$), whereas sensitivity was not significant ($p = 0.10047$). For KAU, significant differences were observed for precision ($p = 0.00158$) and specificity ($p = 0.00304$); accuracy ($p = 0.06234$), sensitivity ($p = 0.49024$), and F1-score ($p = 0.09574$) did not reach the 0.05 significance level. For metrics with a significant Friedman result, two-sided Wilcoxon signed-rank tests were subsequently applied to the paired fold-level scores. As defined in Eq. (31), the Bonferroni-corrected significance threshold was 0.00333 for the 15 pairwise comparisons. No individual pairwise comparison remained significant after this correction. Accordingly, VG-NVG-PSD-SVM on Banda Aceh and VG-HVG-PSD-SVM on KAU are interpreted as the best observed configurations based on mean fold-level performance, rather than statistically superior methods.

Table 1. Classification performance of the six feature-classifier configurations on the Banda Aceh and KAU EEG datasets.

Dataset	Feature	Classifier	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
Banda Aceh	VG-NVG-PSD	SVM	97.14 ± 3.29	100.00 ± 0.00	94.27 ± 6.58	100.00 ± 0.00	96.95 ± 3.59
Banda Aceh	PSD	SVM	96.17 ± 3.68	98.54 ± 1.82	93.78 ± 7.79	98.57 ± 1.78	95.92 ± 4.23
Banda Aceh	VG-NVG-PSD	MLP	95.93 ± 1.61	98.52 ± 1.85	93.27 ± 3.30	98.57 ± 1.78	95.78 ± 1.69
Banda Aceh	PSD	MLP	95.68 ± 2.16	95.50 ± 5.05	96.17 ± 3.00	95.24 ± 5.73	95.71 ± 1.98
Banda Aceh	VG-HVG-PSD	SVM	87.28 ± 4.51	92.22 ± 9.78	83.07 ± 10.60	91.43 ± 11.36	86.52 ± 4.86
Banda Aceh	VG-HVG-PSD	MLP	84.64 ± 5.36	88.34 ± 8.17	81.64 ± 16.91	87.62 ± 9.95	83.35 ± 7.40
KAU	VG-HVG-PSD	SVM	96.83 ± 2.34	97.83 ± 2.99	95.54 ± 5.23	97.99 ± 2.78	96.56 ± 2.56
KAU	PSD	SVM	96.48 ± 3.88	100.00 ± 0.00	92.56 ± 8.23	100.00 ± 0.00	95.96 ± 4.62
KAU	PSD	MLP	94.36 ± 4.73	98.48 ± 2.81	89.61 ± 10.74	98.68 ± 2.44	93.45 ± 5.85
KAU	VG-NVG-PSD	SVM	93.61 ± 3.32	93.39 ± 6.79	93.84 ± 6.68	93.20 ± 7.69	93.28 ± 3.42
KAU	VG-NVG-PSD	MLP	91.84 ± 3.23	90.42 ± 6.21	93.24 ± 5.02	90.46 ± 7.18	91.58 ± 2.98
KAU	VG-HVG-PSD	MLP	90.06 ± 6.98	91.01 ± 10.64	89.52 ± 8.87	90.68 ± 13.71	89.62 ± 6.57

Their numerical gains over PSD-SVM should therefore be considered together with inter-fold variability and the corrected statistical results.

while retaining regularization control [31], which can be advantageous when the number of independent participants is limited. In contrast, the six-hidden-layer

Table 2. Friedman omnibus test results for five performance metrics across the six feature–classifier configurations.

Dataset	Metric	Friedman statistic, (χ_F^2)	df	p-value	Decision at ($\alpha = 0.05$)
Banda Aceh	Accuracy	23.7076	5	0.00025	Significant
Banda Aceh	Precision	13.7260	5	0.01745	Significant
Banda Aceh	Sensitivity	9.2237	5	0.10047	Not significant
Banda Aceh	Specificity	13.1378	5	0.02212	Significant
Banda Aceh	F1-score	19.6694	5	0.00144	Significant
KAU	Accuracy	10.4962	5	0.06234	Not significant
KAU	Precision	19.4589	5	0.00158	Significant
KAU	Sensitivity	4.4231	5	0.49024	Not significant
KAU	Specificity	17.9263	5	0.00304	Significant
KAU	F1-score	9.3542	5	0.09574	Not significant

IV. Discussion

A. Interpretation of Graph-Spectral Performance

The results indicate that visibility-graph representations of EEG PSD curves can provide complementary discriminatory information beyond conventional spectral descriptors, although their effectiveness depends on the visibility criterion and dataset. In Banda Aceh, VG-NVG-PSD-SVM achieved the best observed accuracy of $97.14 \pm 3.29\%$, corresponding to a numerical improvement of 0.97 percentage points over PSD-SVM. On KAU, VG-HVG-PSD-SVM achieved $96.83 \pm 2.34\%$, with a 0.35-percentage-point accuracy improvement and a 2.98-percentage-point sensitivity improvement relative to PSD-SVM. These findings are consistent with the different structural properties of NVG and HVG. NVG preserves both local and longer-range geometric relationships among spectral samples, whereas HVG applies a stricter visibility criterion and generally produces a sparser topology [15], [16], [17]. Consequently, the two graph constructions may emphasize different aspects of PSD geometry. Their different behavior on Banda Aceh and KAU suggests that the most informative visibility representation depends on characteristics of the underlying EEG spectral structure rather than on one graph rule being universally superior. Differences in sampling frequency, channel configuration, acquisition equipment, recording duration, participant characteristics, and recording environment may also contribute to the dataset-dependent results. Although identical frequency bands, PSD settings, graph measures, and classifiers were applied, these acquisition characteristics can still influence PSD geometry and the resulting graph topology. The substantially lower VG-HVG-PSD performance on Banda Aceh further shows that graph transformation does not inherently improve classification; its benefit depends on whether the resulting topology preserves discriminative spectral relationships.

B. Classifier and Statistical Interpretation

SVM produced the highest observed configuration on both datasets. The RBF kernel can represent nonlinear decision boundaries in high-dimensional feature spaces

MLP contains substantially more trainable parameters and may require larger independent cohorts to learn equally stable participant-independent patterns [32]. This does not imply that neural networks are unsuitable for ASD EEG analysis, because high performance has been reported using convolutional and time-frequency deep-learning representations [11], [12], [13], [14]. The results also demonstrate the importance of considering multiple performance metrics. On Banda Aceh, PSD-MLP achieved the highest sensitivity, whereas VG-NVG-PSD-SVM provided the highest accuracy, precision, specificity, and F1-score. On KAU, VG-HVG-PSD-SVM improved sensitivity over PSD-SVM while maintaining high precision and specificity. Therefore, accuracy alone does not fully describe the performance characteristics of each representation. Statistical analysis further supports a cautious interpretation. Although Friedman testing identified global differences among the six configurations for several metrics, no pairwise Wilcoxon comparison remained significant after Bonferroni correction. Consequently, the graph-based SVM configurations should be interpreted as **numerically best observed results rather than statistically established superiority**. The relatively small numbers of seven and eight paired outer folds also limit the statistical power available for post-hoc comparisons.

C. Comparison with Previous EEG-Based ASD Studies

The present results are compared with selected EEG-based ASD classification studies in Table 3. Because these studies differ in participant cohorts, feature representations, classifiers, and validation designs, the comparison is intended to provide methodological context rather than a direct ranking of reported accuracies. As shown in Table 3, high EEG-based ASD classification performance has been obtained using diverse representations. The hybrid lightweight feature approach in [11] achieved 96.44% accuracy using SVM, while the spectrogram-based CNN in [13] reported 99.15%. TFSNet [14] achieved 98.68% on the Sheffield dataset and 97.14% on KAU, whereas the FFT-FLDA approach in [21] reported a best correct rate of 91.64% under 10-fold

cross-validation. Connectivity-based graph features have also achieved 95.80% accuracy [36], illustrating that graph-related representations can capture diagnostically relevant EEG organization. In addition, grid-tuned ensemble learning based on 2D spectrograms reported 94.71% accuracy on KAU and 96.22% on TUOS [37], further demonstrating the range of spectral and time-frequency representations explored for ASD classification. Beyond maximizing classification accuracy, computational efficiency is also relevant for future practical implementation. Energy-efficient EEG-based ASD detection using wearable sensing has been investigated in [38], indicating broader interest in lightweight processing pipelines suitable for resource-constrained systems. In this context, the present use of fixed-length graph-spectral features with SVM may offer a useful direction for further development of computationally efficient EEG screening-support frameworks. The present accuracies of 97.14% on Banda Aceh and 96.83% on KAU are within the range reported in previous studies. Nevertheless, direct accuracy ranking is inappropriate because participant numbers, validation units, and partitioning strategies differ substantially. In particular, sample- or image-level partitioning provides different evidence of generalization from participant-disjoint testing. The main contribution of this study is a controlled comparison of direct PSD, NVG-PSD, and HVG-PSD using identical preprocessing, classifiers, and held-out participant folds across two independently evaluated EEG datasets.

D. Practical Implications, Limitations, and Future Work

From a practical perspective, PSD-derived visibility graphs can be incorporated after conventional PSD estimation and yield fixed-length handcrafted features associated with specific EEG channels, frequency bands, and graph-topological measures. Their strong observed

performance with RBF-SVM supports further investigation of relatively lightweight and interpretable EEG classification frameworks. However, the present findings should not be interpreted as evidence of clinical diagnostic readiness. The primary limitation is the small number of independent participants: 14 in Banda Aceh and 16 in KAU. Consequently, individual held-out participants can substantially influence fold-level performance, and the numerical improvements of 0.97 and 0.35 percentage points should be interpreted together with inter-fold variability and the corrected statistical results. This concern is particularly relevant because larger resting-state EEG investigations have reported relatively sparse and heterogeneous ASD-related differences, highlighting the influence of cohort size and participant variability on reproducibility [39]. Although outer testing was participant-disjoint, the reported metrics were calculated at the epoch level. The results therefore characterize classification of EEG epochs from unseen participants rather than one aggregated diagnostic decision per participant. Future larger-cohort investigations should complement epoch-level analysis with participant-level decision aggregation and subject-level performance reporting. Feature dimensionality also differed across representations: direct PSD contained 800 features, whereas VG-NVG-PSD and VG-HVG-PSD each contained 640. Therefore, the observed differences cannot be attributed exclusively to graph topology. Dimensionality-controlled comparisons and feature-stability analyses would help distinguish the contribution of topology from that of representation size.

Automated ICA-based artifact removal and bad-channel interpolation were not applied because equivalent artifact annotations and channel-quality information were unavailable across both datasets. A consistent preprocessing pipeline reduced procedural differences, although residual physiological or non-

Table 3. Comparison of the proposed method with selected EEG-based ASD classification studies.

Ref.	Dataset / participants	Representation	Classifier	Validation	Sensitivity / Specificity	Accuracy
[11]	61 ASD + 61 controls	1D-LBP-STFT + hybrid lightweight deep features	SVM	10-fold CV	NR / NR	96.44%
[13]	KAU: 12 ASD + 4 controls	STFT spectrogram	CNN	70/15/15 train-validation-test image split	99.19% / 99.04%	99.15%
[14]	Sheffield: 28 ASD + 28 controls; KAU: 12 ASD + 5 controls	Time-frequency synergy representation	TFSNet	5-fold CV	NR / NR	98.68% Sheffield; 97.14% KAU
[21]	8 ASD + 4 controls	Raw EEG and FFT features	FLDA	10-fold CV	NR / NR	91.64%
[36]	12 ASD + 12 TD	PLV connectivity + graph measures	Cubic SVM	NR	100% / 92%	95.80%
[37]	KAU and TUOS datasets	2D spectrogram + grid-tuned ensemble	Ensemble learning	Dataset-specific evaluation	NR / NR	94.71% KAU; 96.22% TUOS
Present study	Banda Aceh: 7 ASD + 7 TD; KAU: 8 ASD + 8 controls	Direct PSD and PSD-derived NVG/HVG	RBF-SVM	7-/8-fold subject-wise balanced CV	BA: 94.27% / 100.00%; KAU: 95.54% / 97.99%	97.14% BA; 96.83% KAU

NR: not reported or not sufficiently specified for direct comparison

physiological artifacts may remain. Demographic differences in age and sex composition may likewise contribute to EEG variability and cannot be fully separated from diagnostic effects in these small cohorts. The two datasets were also evaluated independently, without direct cross-dataset model transfer. The present findings therefore demonstrate within-dataset generalization to unseen participants but do not establish cross-center or cross-device transferability. Future work should investigate larger demographically balanced multicenter cohorts, dimensionality-controlled comparisons, participant-level evaluation, and external cross-dataset validation. Interpretability analysis should also be extended beyond predefined graph measures to examine whether the features driving classifier decisions correspond to plausible neurophysiological patterns. Previous work has demonstrated the value of interpretability analysis for EEG-based deep-learning models in autism-related cohorts [40], supporting its inclusion in future ASD classification frameworks.

V. Conclusion

This study evaluated whether visibility-graph topology derived from EEG PSD curves provides complementary information beyond conventional spectral descriptors for ASD classification. Direct PSD, VG-NVG-PSD, and VG-HVG-PSD were compared using RBF-SVM and MLP under subject-wise balanced cross-validation, with epoch-level performance evaluated exclusively on held-out participants. VG-NVG-PSD with SVM produced the best observed accuracy of $97.14 \pm 3.29\%$ on Banda Aceh, representing a numerical improvement of 0.97 percentage points over PSD-SVM, whereas VG-HVG-PSD with SVM achieved $96.83 \pm 2.34\%$ on KAU, representing a 0.35-percentage-point improvement. The preferred visibility criterion depended on the dataset, and graph transformation did not improve every feature-classifier configuration. Although the Friedman analysis identified global differences for several metrics, no individual pairwise comparison remained significant after Bonferroni correction; therefore, the observed advantages should be interpreted as numerical rather than statistically established superiority. Overall, PSD-derived visibility graphs provide an interpretable complementary representation for EEG-based ASD classification and can be integrated with conventional spectral processing and lightweight classifiers. However, the small cohorts, epoch-level performance reporting, unequal feature dimensionality, demographic differences, and absence of cross-dataset testing limit broader generalization. Larger multicenter cohorts, participant-level decision evaluation, dimensionality-controlled analyses, and external validation are required before translation to clinical screening-support settings.

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Declarations

Ethics Approval

The Banda Aceh EEG data used in this study were obtained from a previously approved study. Ethical approval for the original data collection was granted by the Health Research Ethics Committee under approval No. 117/EA/FK/2024. The present study involved secondary analysis of previously collected EEG recordings and did not involve additional participant recruitment.

Consent to Participate

Informed consent was obtained from all participants and, where applicable, from their parents or legal guardians during the original data collection in accordance with the approved ethical protocol. The present study involved only secondary analysis of previously collected EEG recordings and did not involve new participant recruitment.

Consent for Publication

Not applicable. No identifiable individual participant information, images, or personal data are presented in this manuscript.

Data Availability

The Banda Aceh EEG data analyzed in this study are available from the corresponding author upon reasonable request and subject to applicable ethical and institutional requirements. Requests may be directed to Melinda Melinda at melinda@usk.ac.id. The KAU EEG dataset was obtained from King Abdulaziz University Hospital, Jeddah, Saudi Arabia, and is available from the original data provider subject to permission.

Competing Interests

The authors declare that they have no competing interests.

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Author Contributions

Muhammad Saifullah Nur contributed to methodology development, EEG data processing, feature extraction, software implementation, experimental analysis, visualization, and preparation of the original manuscript. Melinda Melinda contributed to conceptualization, methodology, supervision, resources, project administration, interpretation of results, and manuscript review and editing. Yuwaldi Away contributed to supervision, methodology, technical validation, interpretation, and manuscript review. Siti Rusdiana contributed to methodological and statistical evaluation, validation, interpretation, and manuscript review. Souvik Das contributed to methodological review, interpretation, and critical revision. Zulfan Zulfan contributed to computational methodology, validation, interpretation, and manuscript review. All authors reviewed and

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Use of Generative AI and AI-Assisted Technologies in Writing

AI-assisted tools were used during manuscript preparation for language editing and improving clarity and readability. All AI-assisted content was reviewed and revised by the authors, who take full responsibility for the final manuscript.

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Author Biography



Muhammad Saifullah Nur was born in Punie, Aceh Besar, Indonesia. He received his B.Eng. degree from the Department of Electrical and Computer Engineering, Faculty of Engineering, Universitas Syiah Kuala, Banda Aceh. He is currently pursuing a Master's degree in Electrical Engineering at Universitas Syiah Kuala with a concentration in Biomedical Systems and Signal Processing. His graduate research focuses on EEG signal processing for neurodevelopmental disorder analysis, including time-frequency decomposition, feature extraction, and machine learning models such as CNN-LSTM and graph-based approaches for classification and early detection. During his studies, he has been actively involved as a laboratory assistant in the Telecommunications and Multimedia Laboratory and has participated in various research, innovation, and training programs at the national level. His research interests include biomedical signal processing, EEG-based brain-computer interfaces, deep learning for healthcare, and knowledge management systems to support clinical decision-making. He can be contacted at email: msaifullah@mhs.usk.ac.id



Melinda was born in Bireuen, Aceh, on June 10, 1979. She received a B.Eng. degree from the Department of Electrical and Computer Engineering, Faculty of Engineering, Universitas Syiah Kuala, Banda Aceh in 2002. She completed her master's degree at the Faculty of Electrical Department, University of Southampton, United Kingdom, with a concentration in field study of Radio Frequency Communication Systems in 2009. She received her doctoral degree at the Department of Electrical Engineering, Faculty of Engineering, Universitas Indonesia, in February 2018. She has been with the Department of Electrical Engineering, Faculty of Engineering, Universitas Syiah Kuala since 2002. Her research interests include multimedia signal processing and fluctuation processing. She can be contacted at email: melinda@usk.ac.id.



Yuwaldi Away (Member, IEEE) was born in South Aceh, Indonesia, in 1964. He earned his degree in Electrical-Computer Engineering from Sepuluh Nopember Institute of Technology (ITS), Indonesia, in 1988, followed by an M.Sc. degree from Bandung Institute of Technology (ITB), Indonesia, in 1993, and a Ph.D. in industrial computer from the National University of Malaysia (UKM), in 2000. He has been a Lecturer in the Department of Electrical and Computer Engineering, Faculty of Engineering, Universitas Syiah Kuala (USK), Indonesia since 1990. From 1996 to 2000, he was a Research Assistant at UKM, later returning as a lecturer from 2001 to 2004. Since 2007, he has held the position

of Professor and serves as Head of the Research Group for Automation and Robotics Studies, Syiah Kuala University. His research interests include a combination of theory and practice, including microprocessor-based systems, simulation, automation, and optimization. He can be contacted at email: yuwaldi@usk.ac.id.



Souvik Das completed his B.Tech. in Electrical Engineering from RCC Institute of Information Technology (RCCIIT), West Bengal, India in 2014. He then obtained his M.Tech. in Industrial Engineering and Management from the Indian Institute of Technology (IIT) Kharagpur in 2017. He earned his Ph.D. in Industrial and Systems Engineering from IIT Kharagpur in 2023, where his research focused on data-driven modeling of cognitive workload using eye-tracking metrics. During his doctoral studies, he worked as a Principal Research Scientist at the Centre of Excellence in Safety Engineering and Analytics (CoE-SEA), IIT Kharagpur. He later served as a Postdoctoral Research Fellow (Visiting Scientist) at Purdue University, USA, working on AI-based analysis of accident and incident narratives for safety analytics. Since August 2024, he has been serving as an Assistant Professor in the Department of Industrial Design at the National Institute of Technology (NIT) Rourkela, India. His research interests include human factors, safety analytics, eye-tracking technology, virtual reality, and artificial intelligence for safety and design applications. He can be contacted at rndas9@gmail.com.



Siti Rusdiana was born in Banda Aceh, Indonesia, on 10 September 1963. She received the B.S. degree in mathematics science from Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia, in 1988, the M.Eng. degree in mathematics science from Osaka University, Osaka, Japan, in 1998, and the Ph.D. degree in applied mathematics from Universitas Sumatera Utara, Medan, Indonesia, in 2013. She was the Chairperson of the Department of Mathematics, Universitas Syiah Kuala, Banda Aceh, Indonesia (1998 – 2004). From 2013 to 2020, she was the Head of the Laboratory for Dynamic and Optimization Applications, Department of Mathematics, Universitas Syiah Kuala, where she has been an Associate Professor in the Department of Mathematics since 2014. She is also a member of IEEE. Her research interests in applied mathematics include optimization, operations research, and data science. She can be contacted at email: siti.rusdiana@usk.ac.id.



Zulfan Zulfan was born in Bambi, Pidie, Aceh, Indonesia, in 1986. He received the B.Sc. degree in mathematics science from Universitas Syiah Kuala, Indonesia, in 2010, and the M.Sc. degree in information technology from Universiti Utara Malaysia, Kedah Darul Aman, Malaysia, in 2013. Since 2015,

he has been a Lecturer and a Research Assistant with the Data and Computer Networking Laboratory, Department of Informatics, Universitas Syiah Kuala, where he has been an Assistant Professor with the Department of Informatics since 2019. He is also the author of

publications in international journals and conference proceedings, such as the 2021 Sixth International Conference on Informatics and Computing (ICIC), the International Conference on Information Technology and Education 2018 (ICITED 2018), and the 7th AIC-ICMR on Sciences and Engineering 2017. His research interests include parallel computing, embedded systems, and artificial intelligence. Mr. Zulfan was a recipient of an Aceh Government Scholarship, in 2011, and a member of the Association of Higher Education of Informatics and Computer (APTİKOM). He can be contacted at email: zulfan.abdullah@usk.ac.id.