

Supplementary Information for

ReHA-Net: A ReVIN–Hybrid Attention Network With Multiscale Convolution for Robust EEG Artifact Removal in Brain–Computer Interfaces

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Section S1 — Evaluation under Low-SNR Conditions

To complement the main results, an additional analysis was carried out to assess the robustness of ReHA-Net under severely degraded signal conditions. The input EEG signals were evaluated at SNR levels ranging from -10 dB to 0 dB, simulating real-world scenarios involving strong ocular and muscular artifacts. Detailed quantitative outcomes are summarized in Table S1, and the performance trend across different SNR levels is illustrated in Figure S1.

Table S1. Quantitative evaluation of ReHA-Net at low input SNR levels.

Input SNR (dB)	PSNR (dB)	Output SNR (dB)	CC	RRMSE
-10	0.27	-10.00	0.26	2.52
-7	6.04	-4.23	0.45	1.36
-5	9.60	-0.66	0.60	0.94
-3	12.65	2.39	0.73	0.69
-1	15.03	4.76	0.83	0.54
0	16.03	5.77	0.87	0.48

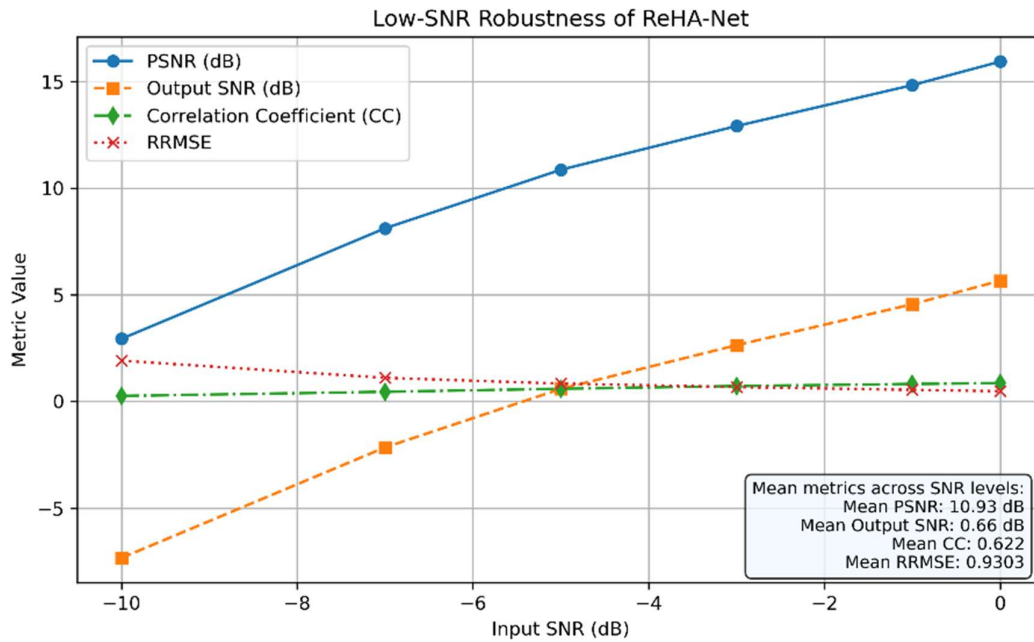


Figure S1. Performance trend of ReHA-Net across low input SNR levels (-10 dB to 0 dB). The plot shows a gradual increase in PSNR, SNR, and correlation coefficients, and a steady decrease in RRMSE, indicating improved reconstruction quality as noise level decreases.

Section S2 — Comparison with Existing EEG Denoising Models

To demonstrate the advantages of ReHA-Net, its performance was compared against state-of-the-art EEG denoising methods. Table S2 summarizes the mean $\pm$ standard deviation (SD) of RRMSE for EOG and EMG artifact removal. ReHA-Net shows superior denoising performance compared to existing methods across both EOG and EMG artifacts.

Table S2. Mean $\pm$ SD of RRMSE values for different EEG denoising models.

Model	EOG RRMSE	EMG RRMSE
DeepSeparator (2022)	0.378 ± 0.005	0.478 ± 0.005
DuoCL (2022)	0.309 ± 0.015	0.332 ± 0.013
EEGDNet (2022)	0.270 ± 0.010	0.431 ± 0.010
NovelGAN (2022)	0.317 ± 0.004	0.448 ± 0.005
GCTNet (2023)	0.264 ± 0.001	0.286 ± 0.010
EEGDiR (2024)	0.278 ± 0.009	0.311 ± 0.009
EEGIFNet (2024)	0.215 ± 0.007	0.343 ± 0.006
MSCGRU (2025)	0.246 ± 0.010	0.277 ± 0.009
Proposed RehaNet (2025)	0.165 ± 0.006	0.172 ± 0.007

Section S3 — Sensitivity Analysis of Loss Weighting Factors

To assess ReHA-Net’s robustness to the combined loss function, we conducted a sensitivity analysis on the correlation (λ_{CC}) and spectral-domain (λ_{PSD}) weighting factors. Table S3 reports performance metrics (PSNR, SNR, CC, RRMSE) across multiple λ_{CC} and λ_{PSD} combinations, showing minimal variation and confirming model stability. Figure S2 presents the validation loss heatmap, illustrating that performance is largely insensitive to moderate weighting changes. The selected configuration ($\lambda_{CC} = 0.05$, $\lambda_{PSD} = 0.05$) lies in a stable region, balancing temporal correlation preservation and spectral regularization.

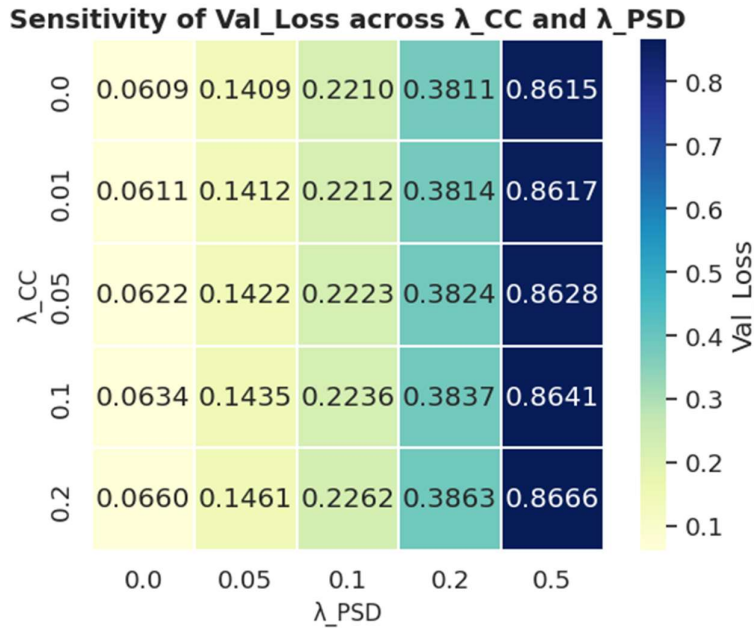


Figure S2. Validation loss heatmap across λ_{CC} and λ_{PSD} configurations. The nearly uniform loss distribution confirms that model performance is insensitive to moderate variations in loss weighting. The selected configuration lies within a stable region, supporting its empirical selection.

Table S3. Sensitivity analysis of λ_{CC} and λ_{PSD} weighting factors.

λ_{CC}	λ_{PSD}	Train Loss	Val Loss	PSNR	SNR	CC	RRMSE
0.00	0.00	0.0598	0.0609	24.7432	14.7059	0.9742	0.1954
0.00	0.05	0.1382	0.1409	24.7432	14.7059	0.9742	0.1954
0.00	0.10	0.2165	0.2210	24.7432	14.7059	0.9742	0.1954
0.00	0.20	0.3733	0.3811	24.7432	14.7059	0.9742	0.1954
0.00	0.50	0.8436	0.8615	24.7432	14.7059	0.9742	0.1954
0.01	0.00	0.0600	0.0611	24.7432	14.7059	0.9742	0.1954
0.01	0.05	0.1384	0.1412	24.7432	14.7059	0.9742	0.1954
0.01	0.10	0.2168	0.2212	24.7432	14.7059	0.9742	0.1954
0.01	0.20	0.3735	0.3814	24.7432	14.7059	0.9742	0.1954
0.01	0.50	0.8439	0.8617	24.7432	14.7059	0.9742	0.1954
0.05	0.00	0.0610	0.0622	24.7432	14.7059	0.9742	0.1954
0.05	0.05	0.1393	0.1422	24.7432	14.7059	0.9742	0.1954
0.05	0.10	0.2177	0.2223	24.7432	14.7059	0.9742	0.1954
0.05	0.20	0.3745	0.3824	24.7432	14.7059	0.9742	0.1954
0.05	0.50	0.8447	0.8628	24.7432	14.7059	0.9742	0.1954
0.10	0.00	0.0621	0.0634	24.7432	14.7059	0.9742	0.1954
0.10	0.05	0.1405	0.1435	24.7432	14.7059	0.9742	0.1954
0.10	0.10	0.2189	0.2236	24.7432	14.7059	0.9742	0.1954
0.10	0.20	0.3756	0.3837	24.7432	14.7059	0.9742	0.1954
0.10	0.50	0.8459	0.8641	24.7432	14.7059	0.9742	0.1954
0.20	0.00	0.0645	0.0660	24.7432	14.7059	0.9742	0.1954
0.20	0.05	0.1428	0.1461	24.7432	14.7059	0.9742	0.1954
0.20	0.10	0.2212	0.2262	24.7432	14.7059	0.9742	0.1954
0.20	0.20	0.3780	0.3863	24.7432	14.7059	0.9742	0.1954
0.20	0.50	0.8483	0.8666	24.7432	14.7059	0.9742	0.1954

Section S4 — Performance Across Random Seeds

To evaluate stability and reproducibility, ReHA-Net was tested across four random seeds (42, 123, 999, 2025). Table S4 summarizes key performance metrics (PSNR, SNR, CC, RRMSE, EOG-RRMSE, EMG-RRMSE), showing consistent results across runs. Figure S3 illustrates variability, with error bars representing $\pm$ standard deviation, confirming that ReHA-Net provides stable and reproducible denoising performance.

Table S4. ReHA-Net performance across different random seeds.

Metric	Seed 42	Seed 123	Seed 999	Seed 2025	Mean $\pm$ SD
PSNR (dB)	25.03	25.87	25.57	25.33	25.45 $\pm$ 0.27
SNR (dB)	15.00	15.83	15.53	15.29	15.41 $\pm$ 0.31
CC	0.967	0.975	0.973	0.964	0.970 $\pm$ 0.004
RRMSE	0.2019	0.1801	0.1869	0.2076	0.194 $\pm$ 0.012
EOG-RRMSE	0.2018	0.1852	0.1818	0.2140	0.196 $\pm$ 0.013
EMG-RRMSE	0.1945	0.1878	0.1870	0.2133	0.196 $\pm$ 0.011

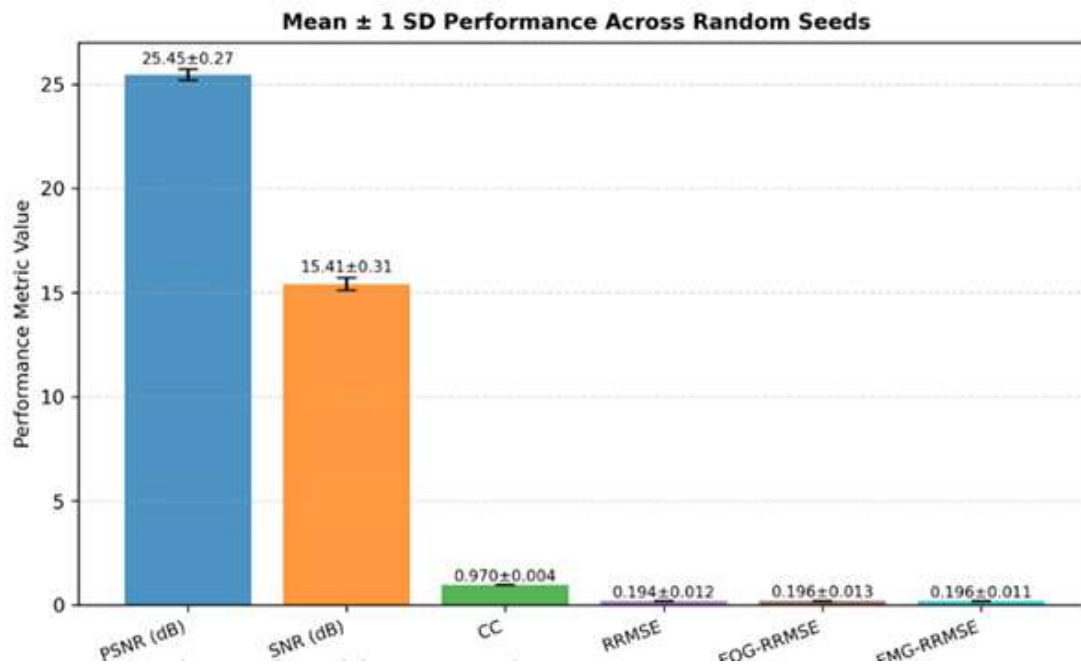


Figure S3. Performance variability of ReHA-Net across four random seeds (42, 123, 999, 2025). Bars represent mean values for each performance metric, and error bars denote $\pm$ standard deviation across runs, showing stable and reproducible performance.