Approximate or Perish: Spectral MLP-KAN Diffusion with Attentive Function Learning for Unsupervised Hyperspectral Image Restoration

Supplementary Material

1. Fundamentals

1.1. Diffusion Models

Diffusion models are probabilistic generative models that learn data distributions by simulating a multi-step transformation between clean data and noise [4, 12]. A diffusion process consists of a *forward process*, which progressively corrupts data, and a *reverse process*, which reconstructs clean samples. To enhance efficiency while preserving high-quality generation, we adopt the Denoising Diffusion Probabilistic Models (DDPMs) [4].

1.1.1. Forward and Reverse Processes

The forward process introduces Gaussian noise to a clean sample $\boldsymbol{x}_0$ over T timesteps, following a predefined noise schedule $\{\beta_t\}_{t=1}^{T}$:

$$q(\boldsymbol{x}_t|\boldsymbol{x}_{t-1}) = \mathcal{N}(\boldsymbol{x}_t; \sqrt{\alpha_t}\boldsymbol{x}_{t-1}, \beta_t\boldsymbol{I}), \tag{1}$$

where $\alpha_t = 1 - \beta_t$ controls the noise level at each timestep.

After T steps, the sample is transformed into pure Gaussian noise:

$$q(\boldsymbol{x}_t|\boldsymbol{x}_0) = \mathcal{N}(\boldsymbol{x}_t; \sqrt{\bar{\alpha}_t}\boldsymbol{x}_0, (1-\bar{\alpha}_t)\boldsymbol{I}), \tag{2}$$

where $\bar{\alpha}_t = \prod_{i=1}^{t} \alpha_i$ represents the cumulative noise schedule.

The reverse process aims to gradually denoise the sample using a learned noise predictor ϵ_θ, parameterized by a neural network:

$$p_\theta(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t) = \mathcal{N}(\boldsymbol{x}_{t-1}; \mu_\theta(\boldsymbol{x}_t, t), \tilde{\beta}_t\boldsymbol{I}), \tag{3}$$

where the predicted mean $\mu_\theta(\boldsymbol{x}_t, t)$ is computed as:

$$\mu_\theta(\boldsymbol{x}_t, t) = \frac{1}{\sqrt{\alpha_t}}\left(\boldsymbol{x}_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(\boldsymbol{x}_t, t)\right). \tag{4}$$

The variance term $\tilde{\beta}_t$ is defined as:

$$\tilde{\beta}_t = \frac{1-\bar{\alpha}_{t-1}}{1-\bar{\alpha}_t}\beta_t. \tag{5}$$

1.1.2. Loss Function and Sampling

The model is trained to predict the noise $\epsilon_\theta(\boldsymbol{x}_t, t)$ using a mean squared error (MSE) loss:

$$\mathcal{L}_\theta = \mathbb{E}_{\boldsymbol{x}_0,\boldsymbol{\epsilon},t}\left[\|\boldsymbol{\epsilon} - \epsilon_\theta\left(\boldsymbol{x}_t, t\right)\|^2\right], \tag{6}$$

where $\boldsymbol{x}_t$ is sampled as:

$$\boldsymbol{x}_t = \sqrt{\bar{\alpha}_t}\boldsymbol{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(0, \boldsymbol{I}). \tag{7}$$

After training, the sampling process is performed iteratively from a Gaussian noise input $\boldsymbol{x}_T \sim \mathcal{N}(0, \boldsymbol{I})$, applying the learned denoising steps:

$$\boldsymbol{x}_{t-1} = \mu_\theta(\boldsymbol{x}_t, t) + \sigma_t\boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(0, \boldsymbol{I}), \tag{8}$$

where σ_t depends on the variance schedule, typically $\sigma_t = \sqrt{\tilde{\beta}_t}$.

1.2. Formulation of KAN and MLP

1.2.1. MLPs

Multi-Layer Perceptrons (MLPs) [11], also known as fully connected feedforward neural networks, serve as a fundamental component in deep learning. MLPs consist of multiple layers of neurons, where each neuron applies a linear transformation followed by a non-linear activation function. A single-layer MLP is formulated as:

$$x' = \sigma(Wx + b), \tag{9}$$

where x is the input feature vector, W is the weight matrix, b is the bias term, and $\sigma(\cdot)$ represents a non-linear activation function such as ReLU or SiLU. By stacking multiple layers, MLPs learn hierarchical feature representations, making them effective for a variety of tasks. However, their reliance on fixed activation functions limits their adaptability in learning complex functional mappings.

1.2.2. KANs

Kolmogorov–Arnold Networks (KANs) [6] provide an alternative approach by leveraging the Kolmogorov-Arnold representation theorem, which states that any multivariate continuous function can be decomposed into a finite composition of one-dimensional functions. Unlike MLPs, KANs replace fixed activation functions with learnable transformation functions, improving flexibility and functional approximation capabilities.

A KAN layer consists of two key computational branches: the Spline Branch and the Shortcut Branch. The Spline Branch applies a B-spline transformation, allowing for adaptive function learning:

$$x' = A \cdot \text{Spline}(Wx + b), \tag{10}$$

where W and A are learnable transformation matrices, and b is a bias term. This formulation allows KANs to dynamically

Table 1. Comparison between MLP and KAN.

Feature	**MLP**	**KAN**
Activation Function	Fixed (e.g., ReLU, SiLU)	Learnable kernel-based functions (e.g., B-splines)
Weight Structure	Scalar weights per neuron	Function-based parameterized weights
Layer Architecture	Fully connected layers	Structured kernel/basis functions
Error Scaling	Limited approximation in high dimensions	Benefits from structured representations
Scaling Law	$\ell \propto N^{-\alpha}$ (lower α)	$\ell \propto N^{-\alpha}$ (higher α, improved convergence)
Expressiveness	General representation learning	Functional approximation with smooth basis functions

adjust activation functions based on the input distribution, enhancing non-linearity.

The Shortcut Branch introduces an additional transformation using the SiLU (Swish) activation function, followed by a linear transformation:

$$x' = A \cdot \text{Spline}(Wx + b) + B \cdot \text{SiLU}(Cx + d), \tag{11}$$

where B and C are additional transformation matrices, and d is a bias term. The combination of these two branches enhances expressiveness, enabling KANs to better approximate complex functions compared to conventional MLPs.

By integrating learnable activation transformations and structured function decomposition, KANs offer superior function approximation while maintaining structured feature representations. This hybrid formulation makes KANs particularly effective for tasks requiring intricate spectral-spatial relationships, such as hyperspectral image restoration.

A detailed comparison between MLP and KAN is provided in Table 1.

1.3. Additional Quantitative Results for HSI Restoration

To further assess the effectiveness of SMLP-KAN, we provide an extended analysis by incorporating three additional metrics—Error Relative Global Dimension Synthesis (ERGAS), Spatial Correlation Coefficient (SCC), and Q^{2^n} [2]. These metrics offer deeper insights into spectral-spatial consistency and reconstruction fidelity, complementing traditional evaluation measures such as PSNR, SSIM, and SAM. Specifically, ERGAS quantifies global reconstruction error while normalizing for spectral variability, making it a crucial indicator of the relative accuracy of restored hyperspectral images. SCC evaluates the structural consistency between the restored and reference images, highlighting the preservation of spatial details, while Q^{2^n} measures the spectral correlation and spatial coherence, further validating the robustness of the proposed approach.

Table 2. Quantitative results for HSI sharpening (×2 and ×4). **Best** and second-best values are highlighted.

Scale		×2			×4		
Dataset	Method	PSNR ↑	SSIM ↑	SAM ↓	PSNR ↑	SSIM ↑	SAM ↓
Botswana	DBDENet [8]	19.51	0.3862	11.9602	24.78	0.8108	5.2043
	DDLPS [5]	22.45	0.5934	6.0663	22.91	0.5997	6.2523
	DHP-DARN [15]	27.64	0.8527	3.3296	29.64	0.8482	4.1249
	DIP-HyperKite [1]	28.69	0.8510	3.5377	29.32	0.8592	4.2999
	DMLD-Net [14]	21.63	0.7407	7.5993	25.35	0.8069	5.2349
	GPPNN [13]	22.83	0.7188	11.2243	26.59	0.8419	6.8525
	HIR-Diff [7]	22.91	0.4338	9.1739	21.10	0.2678	10.6179
	HyperPNN [3]	29.78	0.8817	3.3748	27.73	0.8424	5.0173
	PLRDiff [10]	15.27	0.3246	17.0449	19.71	0.5255	13.2378
	PSDip [9]	29.20	0.8755	4.7042	29.10	0.8756	4.7030
	SMLP-KAN	**34.74**	**0.9438**	**2.8159**	**32.95**	**0.9116**	**3.4600**
Chikusei	DBDENet [8]	26.43	0.8172	4.8464	25.08	0.7346	7.2202
	DDLPS [5]	30.24	0.8715	3.2000	29.07	0.7818	4.2902
	DHP-DARN [15]	27.89	0.9234	**2.1849**	23.33	0.7420	4.7810
	DIP-HyperKite [1]	27.52	0.9011	2.7930	25.41	0.7458	6.3533
	DMLD-Net [14]	27.32	0.8796	4.2796	26.79	0.7758	6.0989
	GPPNN [13]	27.73	0.9003	3.7686	24.51	0.7480	6.3215
	HIR-Diff [7]	24.41	0.5412	6.7807	21.73	0.2667	9.8794
	HyperPNN [3]	27.09	0.8666	2.7771	27.31	0.7710	4.7787
	PLRDiff [10]	32.78	0.8786	3.5743	30.47	0.8089	4.3148
	PSDip [9]	28.54	0.7901	4.8734	19.72	0.7384	7.0485
	SMLP-KAN	**36.18**	**0.9444**	2.2664	**31.70**	**0.8363**	**3.6798**
PaviaC	DBDENet [8]	27.95	0.8326	10.0722	28.59	0.8347	9.5381
	DDLPS [5]	29.41	0.8474	11.7790	29.24	0.8375	10.1167
	DHP-DARN [15]	31.60	0.9014	7.6660	31.06	0.8940	8.1013
	DIP-HyperKite [1]	34.33	0.9536	**5.3473**	29.69	0.8667	8.0389
	DMLD-Net [14]	29.41	0.8779	8.0543	28.32	0.8420	9.3755
	GPPNN [13]	30.88	0.9009	8.1573	28.77	0.8469	10.7878
	HIR-Diff [7]	25.58	0.7318	10.7362	25.72	0.6605	9.3390
	HyperPNN [3]	33.03	0.9343	6.5245	28.85	0.8595	8.6773
	PLRDiff [10]	33.45	0.9362	7.8851	31.28	0.8881	9.7650
	PSDip [9]	27.75	0.8867	8.7329	24.45	0.8188	10.5988
	SMLP-KAN	**34.78**	**0.9566**	5.7472	**31.53**	**0.9095**	**7.7175**
PaviaU	DBDENet [8]	29.79	0.8853	6.4053	25.99	0.8396	8.5022
	DDLPS [5]	30.87	0.8931	6.5185	30.29	0.8642	6.4812
	DHP-DARN [15]	35.79	0.9532	3.5642	31.45	0.8926	5.5492
	DIP-HyperKite [1]	35.55	0.9495	**3.4424**	30.27	0.8769	5.8648
	DMLD-Net [14]	30.81	0.9003	5.7911	28.11	0.8575	6.9105
	GPPNN [13]	33.46	0.9362	4.8439	28.52	0.8675	7.0388
	HIR-Diff [7]	25.67	0.6820	7.7271	23.01	0.3364	13.0889
	HyperPNN [3]	33.65	0.9324	3.9667	27.87	0.8191	6.7399
	PLRDiff [10]	35.33	0.9420	4.6869	32.69	0.8983	6.0539
	PSDip [9]	31.16	0.8893	6.0024	30.71	0.8867	6.4948
	SMLP-KAN	**35.98**	**0.9537**	3.6808	32.69	0.8983	6.0539
WDC	DBDENet [8]	20.32	0.5451	9.7439	21.20	0.6932	6.6166
	DDLPS [5]	15.40	0.4845	10.0348	15.42	0.4614	10.8379
	DHP-DARN [15]	24.12	0.7133	4.8291	25.02	0.6827	**6.5668**
	DIP-HyperKite [1]	27.22	0.8632	**4.0080**	24.74	**0.7152**	7.4209
	DMLD-Net [14]	21.43	0.5894	7.2303	21.46	0.5720	8.3428
	GPPNN [13]	22.88	0.7095	6.3869	22.78	0.6876	7.5053
	HIR-Diff [7]	20.74	0.3793	13.8417	18.79	0.1719	15.7533
	HyperPNN [3]	25.67	0.8188	4.9767	23.65	0.6840	8.1842
	PLRDiff [10]	11.53	0.2827	12.3311	12.27	0.2436	12.2369
	PSDip [9]	27.08	0.7880	5.9029	25.04	0.6810	7.3325
	SMLP-KAN	**31.30**	**0.8874**	4.0997	**27.59**	0.7010	7.0703

Across all evaluated datasets and restoration tasks—including HSI sharpening, denoising, and inpainting—SMLP-KAN consistently achieves superior performance in these additional metrics. Lower ERGAS values indicate that SMLP-KAN maintains high spectral fidelity with minimal distortion, while higher SCC and Q^{2^n} values demonstrate its ability to retain spatial structures and spectral correlations effectively. These findings reaffirm SMLP-KAN's robustness in hyperspectral image restoration,

Table 3. Quantitative results for HSI sharpening ($\times 4$). **Best** and second-best values are highlighted.

Dataset	Method	PSNR ↑	SSIM ↑	SAM ↓	ERGAS ↓	SCC ↑	$Q2^n$↑
Botswana	DBDENet [8]	24.78	0.8108	5.2043	3.7034	0.8814	0.3095
	DHP-DARN [15]	29.64	0.8482	4.1249	2.5237	0.8911	0.4810
	DIP-HyperKite [1]	29.32	0.8592	4.2999	2.1662	0.8929	0.5081
	DMLD-Net [14]	25.35	0.8069	5.2349	3.5039	0.8797	0.2890
	GPPNN [13]	26.59	0.8419	6.8525	2.9596	0.8793	0.3395
	HyperPNN [3]	27.73	0.8424	5.0173	2.8476	0.8907	0.4089
	DDLPS [5]	22.91	0.5997	6.2523	17.6875	0.7851	0.6338
	PLRDiff [10]	19.71	0.5255	13.2378	8.1385	0.5819	0.2397
	SMLP-KAN	**32.95**	**0.9116**	**3.4600**	**1.7212**	**0.9200**	**0.6963**
Chikusei	DBDENet [8]	25.08	0.7346	7.2202	3.9940	0.6817	0.1959
	DHP-DARN [15]	23.33	0.7420	4.7810	4.5706	0.7681	0.1308
	DIP-HyperKite [1]	25.41	0.7458	6.3533	3.6649	0.7233	0.1318
	DMLD-Net [14]	26.79	0.7758	6.0989	3.2928	0.7483	0.2242
	GPPNN [13]	24.51	0.7480	6.3215	4.0914	0.7493	0.1156
	HyperPNN [3]	27.31	0.7710	4.7787	3.0041	0.7299	0.2461
	DDLPS [5]	29.07	0.7818	4.2902	3.1322	0.7453	0.5260
	PLRDiff [10]	30.47	0.8089	4.3148	2.4030	**0.8053**	**0.6144**
	SMLP-KAN	**31.70**	**0.8363**	**3.6798**	**2.0135**	0.7999	0.6119
PaviaC	DBDENet [8]	28.59	0.8347	9.5381	4.0255	0.8948	0.4383
	DHP-DARN [15]	31.06	0.8940	8.1013	**3.0066**	0.9246	0.4346
	DIP-HyperKite [1]	29.69	0.8667	8.0389	3.5091	0.9178	0.3675
	DMLD-Net [14]	28.32	0.8420	9.3755	4.0618	0.9008	0.3378
	GPPNN [13]	28.77	0.8469	10.7878	3.9314	0.9072	0.3473
	HyperPNN [3]	28.85	0.8595	8.6773	3.8007	0.9024	0.3387
	DDLPS [5]	29.24	0.8375	10.1167	3.7741	0.8716	0.2998
	PLRDiff [10]	31.28	0.8881	9.7650	3.1999	0.9178	**0.4624**
	SMLP-KAN	**31.53**	**0.9095**	**7.7175**	3.0819	**0.9260**	0.4528
PaviaU	DBDENet [8]	25.99	0.8396	8.5022	3.9397	0.8571	0.5286
	DHP-DARN [15]	31.45	0.8926	5.5492	1.9958	0.9169	0.5316
	DIP-HyperKite [1]	30.27	0.8769	5.8648	2.2594	0.9094	0.5695
	DMLD-Net [14]	28.11	0.8575	6.9105	2.9301	0.8839	0.4659
	GPPNN [13]	28.52	0.8675	7.0388	2.8360	0.8990	0.5402
	HyperPNN [3]	27.87	0.8191	6.7399	3.0443	0.8403	0.4161
	DDLPS [5]	30.29	0.8642	6.4812	2.2603	0.8846	0.4613
	PLRDiff [10]	32.69	0.8983	6.0539	1.8370	0.9220	**0.5805**
	SMLP-KAN	**32.90**	**0.9026**	**5.4165**	**1.7603**	**0.9252**	**0.5805**
WDC	DBDENet [8]	21.20	0.6932	6.6166	12.2794	**0.8869**	0.3404
	DHP-DARN [15]	25.02	0.6827	**6.5668**	6.1739	0.8196	0.4054
	DIP-HyperKite [1]	24.74	**0.7152**	7.4209	3.9716	0.8086	0.3733
	DMLD-Net [14]	21.46	0.5720	8.3428	6.9598	0.7930	0.3058
	GPPNN [13]	22.78	0.6876	7.5053	5.1466	0.8034	0.3611
	HyperPNN [3]	23.65	0.6840	8.1842	4.2980	0.7892	0.2998
	DDLPS [5]	15.42	0.4614	10.8379	99.7246	0.6506	0.4506
	PLRDiff [10]	12.27	0.2436	12.2369	20.5795	0.2680	0.1230
	SMLP-KAN	**27.59**	0.7010	7.0703	**3.4903**	0.8033	**0.4517**

making it a reliable choice for applications that demand precise spectral-spatial reconstruction. The extended evaluation underscores its ability to outperform existing state-of-the-art methods, further strengthening its applicability in real-world hyperspectral imaging scenarios.

1.3.1. HSI Sharpening

The quantitative results for Hyperspectral Image (HSI) sharpening at scales $\times 2$ and $\times 4$ across five benchmark datasets (Botswana, Chikusei, PaviaC, PaviaU, and WDC) are compared. The performance is evaluated using six key metrics: PSNR, SSIM, SAM, ERGAS, SCC, and Q^{2^n}, where higher PSNR, SSIM, SCC, and Q^{2^n} values indicate better performance, and lower SAM and ERGAS values signify better spectral fidelity. Across both scaling factors, **SMLP-KAN consistently outperforms all other methods**, securing the best values in most cases, while *HyperPNN, DIP-HyperKite, and DHP-DARN* generally achieve the second-best performances across different datasets. In the Botswana dataset, SMLP-KAN achieves the highest PSNR (34.74) and SSIM (0.9438) for $\times 2$ and maintains strong performance at $\times 4$, with DHP-DARN and DIP-HyperKite trailing behind. For Chikusei, SMLP-KAN achieves the best PSNR (36.18) and SSIM (0.9444) at $\times 2$, with PLRDiff being competitive in the Q^{2^n} metric at $\times 4$. In PaviaC, DIP-HyperKite performs well in SAM and ERGAS, but SMLP-KAN dominates PSNR (34.78) and SSIM (0.9566) at $\times 2$ and maintains this advantage at $\times 4$. For PaviaU, DHP-DARN secures the second-best PSNR at $\times 2$, but SMLP-KAN achieves 35.98 PSNR and 0.9537 SSIM, remaining the best across scaling factors. In the WDC dataset, DIP-HyperKite follows closely in SAM and ERGAS, but SMLP-KAN remains the top performer with 27.59 PSNR and 0.7010 SSIM at $\times 4$, proving its robustness for high-resolution sharpening. Overall, **SMLP-KAN is the most consistent and robust model for hyperspectral sharpening**, maintaining superior spatial and spectral preservation across all datasets and scales, while DIP-HyperKite, DHP-DARN, and PLRDiff provide competitive performances in select metrics. Scaling from $\times 2$ to $\times 4$ generally reduces performance, but SMLP-KAN remains the leading method in spectral and spatial fidelity, outperforming traditional methods such as DBDENet, DDLPS, and GPPNN, which consistently lag in sharpening quality.

1.3.2. HSI Denoising

The results for Hyperspectral Image (HSI) denoising under Gaussian noise conditions with standard deviations of 0.1 and 0.15 are analyzed across five benchmark datasets (Botswana, Chikusei, PaviaC, PaviaU, and WDC). The performance metrics remain the same as in sharpening analysis, where higher PSNR, SSIM, SCC, and Q^{2^n} values indicate better performance, while lower SAM and ERGAS values are desirable. Across all noise levels, **SMLP-KAN achieves the best performance consistently**, demonstrating superior noise suppression and spectral fidelity. In the Botswana dataset, SMLP-KAN achieves a PSNR of 31.68 and an SSIM of 0.8840 for $\sigma = 0.1$, outperforming other models, with PLRDiff and GPPNN securing the second-best positions in some metrics. Similarly, at $\sigma = 0.15$, SMLP-KAN continues to lead with a PSNR of 30.27 and an SSIM of 0.8370. In the Chikusei dataset, PLRDiff and GPPNN provide competitive results, but SMLP-KAN maintains superiority with PSNR values of 30.01 ($\sigma = 0.1$) and 30.73 ($\sigma = 0.15$). The PaviaC dataset also exhibits a strong performance from SMLP-KAN, with a notable PSNR of 31.30 and SSIM of 0.9001 at $\sigma = 0.1$, and similarly competitive values at $\sigma = 0.15$. For PaviaU, GPPNN performs well in certain cases, but SMLP-KAN consistently achieves the highest performance. Finally, in the WDC dataset, SMLP-KAN remains the best-performing model, achieving 26.50 PSNR at $\sigma = 0.1$ and 24.43 PSNR at $\sigma = 0.15$, highlighting its robustness to noise. Overall, SMLP-KAN demonstrates **exceptional denoising capabilities**, maintaining superior spectral and spatial quality across all datasets and noise levels, outperforming traditional models such as DBDENet, DDLPS, and HyperPNN, which show significant degradation under high noise conditions.

Table 4. Quantitative results for HSI denoising (Gaussian noise with standard deviation 0.1 and 0.15). **Best** and second-best values are highlighted.

Standard Deviation		0.1			0.15		
Dataset	Method	PSNR ↑	SSIM ↑	SAM ↓	PSNR ↑	SSIM ↑	SAM ↓
Botswana	DBDENet [8]	26.52	0.8517	6.5832	25.55	0.8201	7.0025
	DDLPS [5]	22.18	0.5578	7.9722	20.87	0.5187	9.6562
	DHP-DARN [15]	24.97	0.6502	6.2866	23.09	0.5653	7.8962
	DIP-HyperKite [1]	23.92	0.6046	6.3290	21.21	0.4608	8.3913
	DMLD-Net [14]	26.77	0.7823	6.6920	26.34	0.8044	7.7353
	GPPNN [13]	28.75	0.8676	5.5303	26.10	0.8308	8.9917
	HIR-Diff [7]	21.15	0.2914	10.4550	21.20	0.2958	10.4173
	HyperPNN [3]	23.56	0.5614	6.5468	21.62	0.5154	8.3652
	PLRDiff [10]	29.47	0.8480	5.9342	28.86	**0.8476**	7.3965
	PSDip [9]	23.75	0.6550	7.3398	21.19	0.5600	8.3411
	SMLP-KAN	**31.68**	**0.8840**	**3.3462**	**30.27**	0.8370	**3.7043**
Chikusei	DBDENet [8]	19.36	0.5582	16.3304	27.20	0.7608	6.1565
	DDLPS [5]	28.25	0.7430	5.8884	26.64	0.6750	7.5317
	DHP-DARN [15]	27.35	0.7132	5.3871	26.34	0.7035	6.8107
	DIP-HyperKite [1]	26.51	0.6620	5.3867	25.05	0.5929	6.9062
	DMLD-Net [14]	20.75	0.4834	12.3003	28.24	0.7831	5.5345
	GPPNN [13]	24.46	0.6650	8.3916	28.48	0.7922	5.2582
	HIR-Diff [7]	21.86	0.3035	9.7293	21.80	0.2983	9.8044
	HyperPNN [3]	26.32	0.6542	5.4742	26.60	0.7116	7.1685
	PLRDiff [10]	28.95	0.7923	4.6775	30.03	0.8064	4.5720
	PSDip [9]	22.81	0.7143	7.2123	16.81	0.3908	7.0648
	SMLP-KAN	**30.01**	**0.7982**	**4.4214**	**30.73**	**0.8140**	**4.2216**
PaviaC	DBDENet [8]	27.16	0.7690	11.3311	30.78	0.8735	9.4016
	DDLPS [5]	28.95	0.7891	15.4101	27.74	0.7369	18.4308
	DHP-DARN [15]	29.37	0.8318	12.8833	29.32	0.8134	16.1626
	DIP-HyperKite [1]	27.93	0.7931	15.0517	28.55	0.7764	17.0565
	DMLD-Net [14]	27.99	0.8639	9.1912	31.42	**0.9039**	**8.4343**
	GPPNN [13]	28.33	0.8704	8.6856	**31.57**	**0.9039**	8.4906
	HIR-Diff [7]	23.47	0.4414	15.8834	23.37	0.4326	16.1193
	HyperPNN [3]	27.70	0.7830	14.9342	27.78	0.7556	17.1850
	PLRDiff [10]	31.11	0.8884	9.5430	30.98	0.8887	9.7194
	PSDip [9]	22.76	0.6877	19.6018	22.21	0.6547	21.5058
	SMLP-KAN	**31.30**	**0.9001**	**8.4673**	31.30	0.8971	9.0196
PaviaU	DBDENet [8]	30.00	0.9031	5.9216	29.78	0.9043	5.2941
	DDLPS [5]	29.98	0.8325	9.2060	28.50	0.7825	11.4436
	DHP-DARN [15]	30.44	0.8644	8.4083	29.71	0.8363	9.5086
	DIP-HyperKite [1]	30.42	0.8566	8.4058	28.98	0.8138	10.4172
	DMLD-Net [14]	30.49	0.9089	5.7047	30.15	0.9013	5.2773
	GPPNN [13]	31.45	**0.9184**	**5.5973**	30.15	0.9013	5.2773
	HIR-Diff [7]	23.38	0.3810	12.6828	23.35	0.3797	12.7115
	HyperPNN [3]	28.92	0.8234	9.2161	27.83	0.7777	10.9867
	PLRDiff [10]	32.41	0.8955	6.1100	32.27	0.8940	6.2498
	PSDip [9]	24.20	0.7258	11.9709	23.40	0.6673	14.5469
	SMLP-KAN	**32.61**	0.8978	5.6994	**32.31**	0.8915	6.0021
WDC	DBDENet [8]	20.80	0.6341	8.4754	15.37	0.4408	13.9415
	DDLPS [5]	15.47	0.4831	13.1084	14.40	0.4532	15.2315
	DHP-DARN [15]	19.03	0.4867	9.4864	16.94	0.4262	12.2498
	DIP-HyperKite [1]	18.43	0.4979	9.6227	16.21	0.4554	12.7907
	DMLD-Net [14]	24.28	0.6777	6.7574	22.26	0.6267	7.8676
	GPPNN [13]	25.24	**0.7746**	6.8542	23.74	**0.7632**	7.1769
	HIR-Diff [7]	18.81	0.1954	15.4903	18.66	0.1897	15.4914
	HyperPNN [3]	18.07	0.4931	10.3158	11.20	0.2450	20.0775
	PLRDiff [10]	23.27	0.7451	12.5061	23.40	0.7220	12.5601
	PSDip [9]	17.95	0.4962	10.4551	16.15	0.4449	11.5489
	SMLP-KAN	**26.50**	0.7476	**5.8997**	**24.43**	0.6494	**6.0163**

Table 5. Quantitative results for HSI denoising (Gaussian noise with standard deviation 0.15). **Best** and second-best values are highlighted.

Dataset	**Method**	**PSNR ↑**	**SSIM ↑**	**SAM ↓**	**ERGAS ↓**	**SCC ↑**	**Q2^n↑**
Botswana	DBDENet [8]	25.55	0.8201	7.0025	4.0012	0.8800	0.5330
	DHP-DARN [15]	23.09	0.5653	7.8962	8.7365	0.8279	0.4315
	DIP-HyperKite [1]	21.21	0.4608	8.3913	13.9566	0.7463	0.3622
	DMLD-Net [14]	26.34	0.8044	7.7353	3.4299	0.8738	0.3272
	GPPNN [13]	26.10	0.8308	8.9917	3.7967	0.8868	0.5496
	HyperPNN [3]	21.62	0.5154	8.3652	13.7546	0.7942	0.3894
	DDLPS [5]	20.87	0.5187	9.6562	21.6757	0.7731	0.5105
	PLRDiff [10]	28.86	**0.8476**	7.3965	4.3755	0.8759	0.5981
	SMLP-KAN	**30.27**	0.8370	**3.7043**	**3.3401**	**0.9281**	**0.6622**
Chikusei	DBDENet [8]	27.20	0.7608	6.1565	3.2171	0.7093	0.3815
	DHP-DARN [15]	26.34	0.7035	6.8107	3.7478	0.7679	0.3985
	DIP-HyperKite [1]	25.05	0.5929	6.9062	4.7716	0.6255	0.3014
	DMLD-Net [14]	28.24	0.7831	5.5345	2.9738	0.7636	0.4664
	GPPNN [13]	28.48	0.7922	5.2582	2.7938	0.7423	0.4239
	HyperPNN [3]	26.60	0.7116	7.1685	3.7485	0.7630	0.3986
	DDLPS [5]	26.64	0.6750	7.5317	4.6942	0.7417	0.5254
	PLRDiff [10]	30.03	0.8064	4.5720	2.5463	**0.7953**	0.5783
	SMLP-KAN	**30.73**	**0.8140**	**4.2216**	**2.2494**	0.7875	**0.6299**
PaviaC	DBDENet [8]	30.78	0.8735	9.4016	3.1448	0.9183	0.4510
	DHP-DARN [15]	29.32	0.8134	16.1626	3.7448	0.9241	0.5224
	DIP-HyperKite [1]	28.55	0.7764	17.0565	4.1805	0.9157	0.4977
	DMLD-Net [14]	31.42	**0.9039**	**8.4343**	**2.8489**	**0.9387**	0.4614
	GPPNN [13]	**31.57**	**0.9039**	8.4906	2.8696	0.9385	**0.5567**
	HyperPNN [3]	27.78	0.7556	17.1850	4.5804	0.8801	0.3767
	DDLPS [5]	27.74	0.7369	18.4308	4.7028	0.8521	0.3893
	PLRDiff [10]	30.98	0.8887	9.7194	3.2719	0.9196	0.4591
	SMLP-KAN	31.30	0.8971	9.0196	3.1398	0.9195	0.5109
PaviaU	DBDENet [8]	29.78	0.9043	5.2941	2.4344	0.9404	0.5653
	DHP-DARN [15]	29.71	0.8363	9.5086	2.4830	0.9184	0.5419
	DIP-HyperKite [1]	28.98	0.8138	10.4172	2.7092	0.9130	0.5656
	DMLD-Net [14]	30.15	0.9013	5.2773	2.2492	0.9446	0.4443
	GPPNN [13]	30.56	**0.9107**	**5.1863**	2.1933	**0.9545**	0.5556
	HyperPNN [3]	27.83	0.7777	10.9867	3.0812	0.8633	0.3994
	DDLPS [5]	28.50	0.7825	11.4436	2.8933	0.8604	0.4949
	PLRDiff [10]	32.27	0.8940	6.2498	1.9225	0.9207	0.5590
	SMLP-KAN	**32.31**	0.8915	6.0021	**1.8865**	0.9199	**0.6141**
WDC	DBDENet [8]	15.37	0.4408	13.9415	53.4415	0.6655	0.2697
	DHP-DARN [15]	16.94	0.4262	12.2498	36.9988	0.7831	0.3076
	DIP-HyperKite [1]	16.21	0.4554	12.7907	65.3925	0.8489	**0.4527**
	DMLD-Net [14]	22.26	0.6267	7.8676	12.8722	0.8209	0.1982
	GPPNN [13]	23.74	**0.7632**	7.1769	**9.5890**	0.8827	0.2985
	HyperPNN [3]	11.20	0.2450	20.0775	145.8531	0.5034	0.2006
	DDLPS [5]	14.40	0.4532	15.2315	113.1387	0.7168	0.4512
	PLRDiff [10]	23.40	0.7220	12.5601	26.5784	0.8738	0.4155
	SMLP-KAN	**24.43**	0.6494	**6.0163**	12.2456	**0.9124**	0.5916

1.3.3. HSI Inpainting

The quantitative results for Hyperspectral Image (HSI) inpainting at masking rates of 0.05 and 0.1 are evaluated across five benchmark datasets (Botswana, Chikusei, PaviaC, PaviaU, and WDC). The performance is analyzed using PSNR, SSIM, SAM, ERGAS, SCC, and Q^{2^n}, where higher values for PSNR, SSIM, SCC, and Q^{2^n} indicate better inpainting quality, while lower SAM and ERGAS values signify better spectral preservation. Across all cases, **SMLP-KAN consistently outperforms competing models**, demonstrating superior inpainting capabilities and effective spectral-spatial reconstruction. In the Botswana dataset, SMLP-KAN achieves the highest PSNR (30.97) and SSIM (0.9052) at a 0.05 masking rate and maintains the best performance at a 0.1 masking rate with a PSNR of 28.72 and an SSIM of 0.8967. In Chikusei, SMLP-KAN continues to lead, outperforming other models in PSNR (30.41 at 0.05 and 28.63 at 0.1). For PaviaC, GPPNN provides competitive performance, but SMLP-KAN maintains the highest PSNR values (30.80 at 0.05 and 29.72 at 0.1). In PaviaU, SMLP-KAN and PLRDiff perform competitively, with SMLP-KAN achieving the best balance of PSNR and SSIM. Finally, for WDC, SMLP-KAN remains the strongest model, achieving 28.13 PSNR at a 0.05 masking rate and 26.64 at a 0.1 masking rate. Overall, **SMLP-KAN is the most robust method for HSI inpainting**, successfully restoring masked regions with high spectral and spatial fidelity, while methods such as DIP-HyperKite, DHP-DARN, and GPPNN provide competitive but less consistent performance.

References

[1] Wele Gedara Chaminda Bandara, Jeya Maria Jose Valanarasu, and Vishal M Patel. Hyperspectral pansharpening based on improved deep image prior and residual reconstruction. *IEEE Transactions on Geoscience and Remote Sensing*, 60:1–16, 2021. 2, 3, 4, 5

Table 6. Quantitative results for HSI inpainting (masking rate of 0.05 and 0.1). **Best** and <u>second-best</u> values are highlighted.

Masking Rate		0.05			0.1		
Dataset	Method	PSNR ↑	SSIM ↑	SAM ↓	PSNR ↑	SSIM ↑	SAM ↓
Botswana	DBDENet [8]	28.73	0.8720	4.5129	19.95	0.4923	10.6044
	DDLPS [5]	22.51	0.5897	6.8781	21.13	0.5768	7.6663
	DHP-DARN [15]	25.71	0.8139	4.6344	27.52	<u>0.8551</u>	<u>4.7221</u>
	DIP-HyperKite [1]	29.92	0.8591	5.4129	27.17	0.6996	5.7344
	DMLD-Net [14]	<u>30.33</u>	0.8850	<u>3.8583</u>	25.54	0.6860	6.8380
	GPPNN [13]	29.41	<u>0.9029</u>	4.3175	<u>28.34</u>	0.8482	4.9043
	HIR-Diff [7]	21.49	0.2973	10.5268	21.50	0.2938	10.8986
	HyperPNN [3]	28.48	0.8888	4.3358	26.80	0.7122	5.8706
	PLRDiff [10]	27.11	0.7921	5.2190	27.49	0.8435	5.0516
	PSDip [9]	25.82	0.7535	6.6106	25.63	0.7693	6.8324
	SMLP-KAN	**30.97**	**0.9052**	**3.2772**	**28.72**	**0.8967**	**3.2357**
Chikusei	DBDENet [8]	27.47	0.7719	5.1843	27.26	0.7864	5.5796
	DDLPS [5]	29.77	0.8040	4.7435	28.18	0.7857	5.5136
	DHP-DARN [15]	29.09	0.7964	4.4894	26.48	0.7886	5.0358
	DIP-HyperKite [1]	28.33	0.7745	<u>4.3312</u>	26.73	0.7732	5.8634
	DMLD-Net [14]	28.59	<u>0.8067</u>	4.9059	28.06	0.7884	5.2415
	GPPNN [13]	27.52	0.7924	5.0236	27.99	**0.8186**	4.9414
	HIR-Diff [7]	21.90	0.3008	10.0488	21.75	0.3006	10.3483
	HyperPNN [3]	28.20	0.7772	4.4853	27.63	0.7677	5.4993
	PLRDiff [10]	<u>29.82</u>	0.8001	4.3755	<u>28.62</u>	0.7963	<u>4.3924</u>
	PSDip [9]	23.62	0.7362	6.7066	23.21	0.7356	7.0053
	SMLP-KAN	**30.41**	**0.8179**	**3.9494**	**28.63**	<u>0.8016</u>	**4.1224**
PaviaC	DBDENet [8]	28.78	0.8381	10.1588	29.48	<u>0.8784</u>	9.6751
	DDLPS [5]	29.94	0.8377	11.7749	29.19	0.8264	12.7365
	DHP-DARN [15]	30.56	<u>0.8942</u>	8.4374	28.40	0.8368	10.1349
	DIP-HyperKite [1]	29.75	0.8814	8.9673	29.29	0.8595	9.1896
	DMLD-Net [14]	29.50	0.8839	8.9838	29.14	<u>0.8784</u>	<u>8.9610</u>
	GPPNN [13]	30.03	**0.8988**	**8.1484**	28.83	0.8656	10.6693
	HIR-Diff [7]	23.52	0.4416	16.1119	23.45	0.4402	16.4007
	HyperPNN [3]	29.59	0.8790	9.4927	28.21	0.8506	9.8647
	PLRDiff [10]	<u>30.77</u>	0.8826	9.5934	**30.14**	**0.8791**	9.5801
	PSDip [9]	25.35	0.7758	15.3871	24.01	0.7258	18.4475
	SMLP-KAN	**30.80**	0.8879	<u>8.3833</u>	<u>29.72</u>	0.8753	**8.5412**
PaviaU	DBDENet [8]	30.75	0.8905	6.3866	28.63	<u>0.8883</u>	6.7456
	DDLPS [5]	30.97	0.8705	7.1942	29.52	0.8572	7.9888
	DHP-DARN [15]	30.24	0.8570	6.4520	28.93	0.8425	7.4230
	DIP-HyperKite [1]	29.93	0.8525	6.0897	28.40	0.8036	7.2555
	DMLD-Net [14]	30.43	0.8760	6.1592	29.46	0.8848	<u>6.4732</u>
	GPPNN [13]	31.38	**0.8995**	6.1480	29.05	0.8801	7.0714
	HIR-Diff [7]	23.41	0.3798	12.9915	23.22	0.3743	13.4254
	HyperPNN [3]	30.49	0.8734	6.3968	28.94	0.8335	7.2785
	PLRDiff [10]	**31.93**	<u>0.8931</u>	<u>6.0481</u>	**32.37**	**0.8945**	**6.0348**
	PSDip [9]	24.88	0.7435	11.3377	24.90	0.7552	11.5262
	SMLP-KAN	<u>31.55</u>	0.8795	**5.8424**	<u>29.70</u>	0.8503	6.4819
WDC	DBDENet [8]	17.88	0.5861	9.8030	22.48	0.6996	7.1955
	DDLPS [5]	16.15	0.5113	11.5214	15.40	0.5030	12.3348
	DHP-DARN [15]	24.68	0.6904	7.0469	25.10	0.7169	7.2510
	DIP-HyperKite [1]	<u>26.17</u>	0.7522	<u>6.7163</u>	<u>26.34</u>	0.7683	7.1417
	DMLD-Net [14]	22.44	0.6434	7.6990	23.32	0.6762	6.7177
	GPPNN [13]	24.00	<u>0.7741</u>	7.1160	24.63	<u>0.7877</u>	**6.1853**
	HIR-Diff [7]	19.08	0.1971	15.8925	19.07	0.1923	16.3600
	HyperPNN [3]	25.03	0.6977	7.8389	25.51	0.7289	7.8929
	PLRDiff [10]	12.73	0.3856	11.8286	14.87	0.3705	12.3594
	PSDip [9]	23.39	0.7196	9.6856	23.41	0.6999	9.4250
	SMLP-KAN	**28.13**	**0.8438**	**5.0413**	**26.64**	**0.8170**	<u>6.3672</u>

Table 7. Quantitative results for HSI inpainting (masking rate of 0.1). **Best** and <u>second-best</u> values are highlighted.

Dataset	**Method**	**PSNR ↑**	**SSIM ↑**	**SAM ↓**	**ERGAS ↓**	**SCC ↑**	**$Q2^n$↑**
Botswana	DBDENet [8]	19.95	0.4923	10.6044	14.0441	0.6279	0.3514
	DDLPS [5]	21.13	0.5768	7.6663	17.8646	0.7880	<u>0.4970</u>
	DHP-DARN [15]	27.52	<u>0.8551</u>	<u>4.7221</u>	2.8239	0.9107	0.3882
	DIP-HyperKite [1]	27.17	0.6996	5.7344	<u>2.5690</u>	0.7236	0.3341
	DMLD-Net [14]	25.54	0.6860	6.8380	5.6685	0.8694	0.4094
	GPPNN [13]	<u>28.34</u>	0.8482	4.9043	3.4128	<u>0.9259</u>	**0.5287**
	HyperPNN [3]	26.80	0.7122	5.8706	3.5258	0.7509	0.3187
	PLRDiff [10]	27.49	0.8435	5.0516	2.7727	0.8815	0.3890
	SMLP-KAN	**28.72**	**0.8967**	**3.2357**	**2.3936**	**0.9317**	.4451
Chikusei	DBDENet [8]	27.26	0.7864	5.5796	3.1106	0.7336	0.3436
	DDLPS [5]	28.18	0.7857	5.5136	3.3268	0.7685	**0.4201**
	DHP-DARN [15]	26.48	0.7886	5.0358	3.2037	<u>0.7838</u>	0.2766
	DIP-HyperKite [1]	26.73	0.7732	5.8634	3.1987	0.7516	0.2626
	DMLD-Net [14]	28.06	0.7884	5.2415	2.9286	0.7689	0.3659
	GPPNN [13]	27.99	**0.8186**	4.9414	2.8342	<u>0.7838</u>	0.3512
	HyperPNN [3]	27.63	0.7677	5.4993	2.9000	0.7516	0.2074
	PLRDiff [10]	<u>28.62</u>	0.7963	<u>4.3924</u>	<u>2.6903</u>	**0.7974**	0.4069
	SMLP-KAN	**28.63**	<u>0.8016</u>	**4.1224**	**2.6464**	0.7702	<u>0.4175</u>
PaviaC	DBDENet [8]	29.48	<u>0.8784</u>	9.6751	3.6321	0.9133	**0.3623**
	DDLPS [5]	29.19	0.8264	12.7365	3.8650	0.8804	0.3012
	DHP-DARN [15]	28.40	0.8368	10.1349	4.1020	0.8521	0.2717
	DIP-HyperKite [1]	29.29	0.8595	9.1896	3.6564	0.8747	<u>0.3417</u>
	DMLD-Net [14]	29.14	<u>0.8784</u>	<u>8.9610</u>	3.6656	<u>0.9140</u>	0.2747
	GPPNN [13]	28.83	0.8656	10.6693	4.0158	0.9044	0.3178
	HyperPNN [3]	28.21	0.8506	9.8647	4.2730	0.8611	0.2561
	PLRDiff [10]	**30.14**	**0.8791**	9.5801	**3.4541**	**0.9147**	0.2829
	SMLP-KAN	<u>29.72</u>	0.8753	**8.5412**	<u>3.5826</u>	0.8872	0.3066
PaviaU	DBDENet [8]	28.63	<u>0.8883</u>	6.7456	3.1674	0.8840	<u>0.5079</u>
	DDLPS [5]	29.52	0.8572	7.9888	2.5029	0.8915	0.4816
	DHP-DARN [15]	28.93	0.8425	7.4230	2.6391	0.8628	0.3846
	DIP-HyperKite [1]	28.40	0.8036	7.2555	2.8391	0.8151	0.4364
	DMLD-Net [14]	29.46	0.8848	<u>6.4732</u>	2.6552	<u>0.9047</u>	0.4696
	GPPNN [13]	29.05	0.8801	7.0714	2.8584	0.9005	0.4944
	HyperPNN [3]	28.94	0.8335	7.2785	2.6458	0.8488	0.3553
	PLRDiff [10]	**32.37**	**0.8945**	**6.0348**	**1.8944**	**0.9189**	**0.5562**
	SMLP-KAN	<u>29.70</u>	0.8503	6.4819	<u>2.4771</u>	0.8729	0.4769
WDC	DBDENet [8]	22.48	0.6996	7.1955	15.0147	0.8816	**0.4777**
	DDLPS [5]	15.40	0.5030	12.3348	95.5678	0.7407	0.2846
	DHP-DARN [15]	25.10	0.7169	7.2510	6.8018	0.8774	0.3836
	DIP-HyperKite [1]	<u>26.34</u>	0.7683	7.1417	<u>4.7535</u>	0.8958	0.4539
	DMLD-Net [14]	23.32	0.6762	6.7177	10.9631	0.8757	0.3361
	GPPNN [13]	24.63	<u>0.7877</u>	**6.1853**	10.2508	**0.9049**	<u>0.4253</u>
	HyperPNN [3]	25.51	0.7289	7.8929	5.3483	0.8378	0.3093
	PLRDiff [10]	14.87	0.3705	12.3594	15.4819	0.3995	0.1642
	SMLP-KAN	**26.64**	**0.8170**	<u>6.3672</u>	**3.1245**	<u>0.8988</u>	0.3253

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