

Hybrid Learning-Based Multi-Domain Enhancement Framework for Heterogeneous Image Modalities

Mr.D.Jayanth¹, Dr. R. Sankarasubramanian²

¹Research Scholar, Department of Computer Science, Erode Arts & Science College, Erode.

²Research Guide, Department of Computer Science, Erode Arts & Science College, Erode.

Abstract: Medical and environmental images such as MRI, CT, radiographs, retinal fundus photographs, satellite, aerial and hyperspectral scenes are routinely degraded by noise, compressed contrast, haze and uneven illumination. Classical enhancement operators are fast and interpretable but need image-specific parameters, while deep networks are data-hungry, opaque and brittle across modalities. This paper proposes a Hybrid Learning-based Multi-Domain Enhancement (HLMDE) framework that keeps a transparent chain of transform-domain (BM3D) denoising, log-Fourier homomorphic correction, DFT high-frequency emphasis, CLAHE blending and gamma mapping, and learns per image the six parameters that drive it. A 24-dimensional modality-aware descriptor is projected by PCA and clustered by K-means into unsupervised appearance domains; a random forest predicts the relative quality of 82 candidate parameter vectors and selects the best; cluster-balanced augmentation and fitted-Q-iteration reinforcement learning are evaluated as further refinements. On a benchmark of 694 real images from seven modalities and six public sources, with physically motivated degradations, HLMDE raised mean fidelity from 15.22 dB / 0.529 SSIM to 26.44 dB / 0.813 SSIM. It outperformed CLAHE, histogram equalisation, wavelet-CLAHE, fixed-parameter hybrids and an end-to-end patch MLP (+2.80 dB, $p < 10^{-21}$), and matched a strong BM3D baseline overall while exceeding it on Landsat (+1.51 dB), CT and hyperspectral data. Predicting candidate quality instead of regressing parameters contributed +1.05 dB ($p < 10^{-5}$), whereas augmentation and RL refinement gave no significant gain. In leave-one-modality-out tests the learned controller lost 0.75 dB on unseen modalities against 2.14 dB for the MLP. The framework runs on a CPU and returns an auditable parameter log for every image.

Keywords: Image enhancement; medical imaging; remote sensing; hybrid machine learning; random forest; reinforcement learning; domain generalisation; CLAHE; BM3D

1. Introduction

Images are routinely captured in medical and environmental imaging systems which are far from physical best. Magnetic resonance imaging (MRI) at low signal-to-noise ratio, low-dose computed tomography (CT) and radiography accept Rician noise, a low-dose computed tomography (CT) and a radiography suffer from photon-limited Poisson–Gaussian noise, the retinal fundus photograph exhibits strong vignetting and uneven illumination, and satellite, aerial and hyperspectral scenes are corrupted by atmospheric scattering, sensor striping and compressed dynamic range. In all instances the outcome is the same: poor contrast, blunted edges and noise which obscure clinically and environmentally meaningful structure [1].

For the reasons of speed, determinism and auditability, classical enhancement operators are still the mainstay of pipelines that are used regularly in practice. The adaptive

histogram equalisation (AHE) and contrast-limited AHE (CLAHE) methods increase local contrast [2]–[4]; wavelet shrinkage can reduce noise while preserving edges [5]–[7]; and frequency-domain filters in the discrete Fourier transform (DFT) domain can enhance detail or correct illumination by homomorphic filtering [8]. Their disadvantage is that they have free parameters, such as a clip limit, a threshold scale, a gain, a gamma, which are useful for a noisy MRI slice, but not for a hazy aerial tile. Fixed defaults under-enhance or cause artefacts like amplification of noise and formation of haloes.

Deep networks remove the hand-tuning but bring other costs. Convolutional, adversarial and transformer restorers [9]–[13] and the hybrid designs reviewed below [14]–[20] reach high fidelity on the domain they were trained on, yet they need large paired datasets, are expensive to run on edge hardware, behave as black boxes, and degrade when the input modality changes

[21], [22]. In healthcare, paired data are scarce and privacy-restricted, which makes these limitations practical rather than theoretical.

This paper argues that a large part of the benefit of learning can be obtained by learning how to drive interpretable classical operators rather than learning the pixel mapping itself. We propose the Hybrid Learning-based Multi-Domain Enhancement (HLMDE) framework, which keeps a transparent chain of histogram, wavelet and Fourier operators and learns, per image, the six parameters that control it. The learning is organised in three layers: unsupervised discovery of appearance domains, a random-forest quality predictor that selects an initial control vector, and a reinforcement-learning (RL) refiner that adjusts the predicted parameters step by step.

The main contributions are as follows.

A unified hybrid operator chain that couples transform-domain (BM3D) denoising driven by a wavelet noise estimate, log-Fourier homomorphic illumination correction, DFT high-frequency emphasis, CLAHE blending and gamma mapping under a single six-dimensional parameter vector, applicable without change to CT, MRI, X-ray, fundus, satellite, aerial and hyperspectral images.

A modality-aware descriptor of 24 statistical, gradient, spectral and texture features, combined with principal component analysis (PCA) and K-means clustering, that discovers enhancement domains without modality labels and conditions the parameter predictor on soft domain membership.

A cluster-balanced multi-domain augmentation scheme that synthesises additional degraded training pairs for under-represented domains, so that small modalities are not dominated by large ones.

A two-stage parameter controller: a multi-output random forest that predicts the relative quality of 82 candidate control vectors and selects the best one, followed by tree-based fitted Q-iteration that learns a stopping-aware refinement policy over discrete parameter moves.

A reproducible benchmark on 694 real images from seven modalities and six public sources, with modality-

specific physical degradation models, comparison against traditional, denoising and learning-only baselines, ablations, statistical tests and a leave-one-modality-out generalisation study, including the negative finding that augmentation and RL refinement add no significant fidelity on this benchmark.

The remainder of the paper is organised as follows. Section 2 reviews related work. Section 3 describes the framework. Section 4 details the experimental protocol, Section 5 reports and discusses the results, Section 6 states the limitations, and Section 7 concludes.

2. Related Work

2.1 Histogram and transform-domain enhancement

Histogram equalisation redistributes grey levels to flatten the intensity distribution, and its adaptive variants compute the mapping in local tiles [2]. CLAHE limits the slope of the local mapping with a clip limit to avoid noise amplification [3], and it is now standard in mammography, radiography and fundus imaging [4], [30]. Generalisations that interpolate between equalisation and identity mappings were proposed by Stark [31]. Transform-domain methods act on frequency content instead: the wavelet representation of Mallat [5] underlies soft-threshold shrinkage [6] and its subband-adaptive BayesShrink form [7], while homomorphic filtering separates illumination from reflectance in the log-Fourier domain [8]. Non-local collaborative filtering (BM3D) remains one of the strongest classical denoisers [9]. Retinex-style illumination estimation [32], [33] and the dark-channel prior for haze [34] extend the same idea of physically motivated, parameterised correction to low-light and outdoor scenes. These operators are interpretable, but every one of them exposes parameters whose best value depends on the image.

2.2 Learning-based and deep enhancement

Residual CNN denoisers [10], adversarial super-resolution [11] and transformer restorers [12], [13] learn the full mapping from degraded to clean images. Several recent hybrids combine classical and learned stages. Table 1 summarises representative studies, their modality and the limitation that motivates this work.

Table 1. Representative hybrid and learning-based enhancement studies.

Study	Technique	Data and modality	Main finding	Limitation
Rakshit et al. (2022) [14]	CLAHE preprocessing + deep CNN	COVIDx chest X-ray	CLAHE before a CNN raised multi-class lung disease accuracy	Single modality; class imbalance for rare classes
Wang et al. (2023) [15]	Fusion-gate transformer + VAE-GAN	Low-light livestock farm images	Strong brightness and structure recovery in low light	Domain-specific; heavy; fails under extreme underexposure
Rouhbakhshmeghraziz et al. (2025) [16]	Autoencoder-pretrained U-Net + residual blocks + SRGAN	Public low-resolution images	Better fine-detail recovery in super-resolution	Expensive; sensitive to pretraining and residual tuning
Tai et al. (2017) [17]	Random-forest depth estimation	Underwater scenes	Depth-aware attenuation correction improves visibility	Restricted to underwater physics; depth errors propagate
Prabhakar et al. (2024) [18]	ViT autoencoder (ViT-AE++)	BraTS, ACDC, CheXpert (MRI, X-ray)	Better self-supervised medical representations	Long training; low interpretability
Kim and Lee (2022) [19]	Federated deep generative augmentation	Raman spectra	Privacy-preserving synthetic data for distributed sensors	1-D signals only; weak on rare patterns
Jiang et al. (2024) [20]	Retinex + CNN-transformer fusion	LOL, SID low-light	Balances global context and local detail	Memory-intensive; latency; depends on Retinex decomposition

Two trends are visible. First, most systems are trained and evaluated within one modality, and domain shift remains the dominant failure mode of medical image models [21], [22]. Second, the more capable designs are also the heaviest and least transparent.

2.3 Learning the parameters of classical operators

A lighter line of work keeps classical operators and learns their settings. Campos et al. [23] trained regressors to predict CLAHE hyper-parameters from image features, and Tai et al. [17] used random forests to estimate the physical quantity that drives correction. RL has been used to select or sequence enhancement actions: Park et al. [24] learned colour retouching as a sequence of global edits, Yu et al. [25] learned to compose a toolchain of restoration networks, and Furuta et al. [26] applied pixel-wise RL to denoising and restoration. Batch-mode, tree-based RL through fitted Q-iteration

[27] is attractive in this setting because it learns from a fixed set of logged transitions with ensembles of decision trees [28], [29], needs no simulator in the loop at test time and trains in minutes on a CPU.

2.4 Research gap

No existing method combines (i) a single interpretable operator chain spanning histogram, wavelet/transform and Fourier domains, (ii) unsupervised discovery of the appearance domains present in a heterogeneous corpus, (iii) augmentation that balances those domains, and (iv) a one-shot parameter predictor refined by a learned policy. Equally, few studies evaluate a single enhancement model across medical and environmental modalities at once or test it on a modality it has never seen. HLMDE is designed to fill these gaps.

3. Proposed Framework

3.1 Overview

HLMDE maps a degraded grey-level image $x \in [0, 1]^{(N \times N)}$ to an enhanced image $y = E(x; \theta)$, where E is a fixed chain of classical operators and θ is a six-dimensional control vector chosen per image. Learning never touches pixels directly; it decides θ . At inference

the framework (i) computes a modality-aware descriptor of x , (ii) projects it into a learned domain space and computes soft memberships to K discovered domains, (iii) selects an initial control vector from a candidate bank with a random-forest quality predictor, and (iv) refines that vector with a learned Q -function over discrete moves until the policy chooses to stop. Figure 1 shows the data flow.

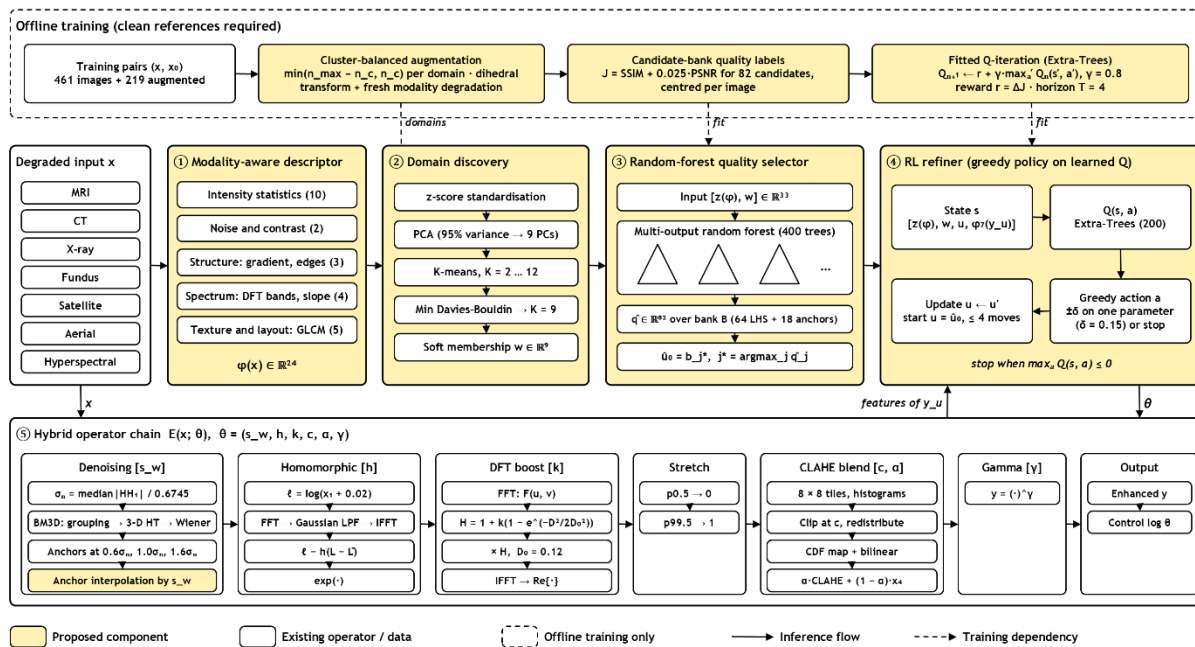


Figure 1. HLMDE architecture · inference path and training-only components

Figure 1. HLMDE architecture. The learned components (top row) only choose the control vector θ ; the enhancement itself is the six-stage classical chain (middle). Dashed links mark components used only during training.

3.2 Hybrid Operator Chain

Let x denote the degraded input image and let $\theta = (s_w, k, h, c, \alpha, \gamma)$ denote the six-dimensional control vector. The normalized control vector u lies in $[0, 1]^6$. Each component is mapped to its admissible parameter range.

$$u = (u_1, u_2, u_3, u_4, u_5, u_6), \quad u_i \in [0, 1] \quad (3.1)$$

$$s_w = 1.6u_1; \quad k = 1.5u_2; \quad h = u_3; \quad \alpha = u_5 \quad (3.2)$$

$$\log c = \log(0.002) + u_4[\log(0.04) - \log(0.002)] \quad (3.3)$$

$$\log \gamma = \log(0.5) + u_6[\log(2) - \log(0.5)] \quad (3.4)$$

Thus c and γ are interpolated in the logarithmic domain, while the remaining parameters use affine mappings. The

enhancement chain consists of transform-domain denoising, homomorphic illumination correction, DFT high-frequency emphasis, robust percentile stretching, CLAHE blending, and gamma mapping.

3.2.1 Transform-Domain Denoising

Estimate the noise scale from the finest diagonal wavelet subband dHH_1 using a median absolute deviation estimator.

$$\hat{\sigma} = \text{median}(|dHH_1|) / 0.6745 \quad (3.5)$$

Let $B_a(x)$ be the BM3D output at anchor strength a , where the denoising threshold is $a\hat{\sigma}$. The anchor set is $\{0.6, 1.0, 1.6\}$; $B_0(x) = x$. For neighbouring anchors $a_i \leq s_w \leq a_{i+1}$, define the interpolation weight:

$$t = (s_w - a_i) / (a_{i+1} - a_i) \quad (3.6)$$

$$x_1 = (1 - t)B_{a_i}(x) + tB_{a_{i+1}}(x) \quad (3.7)$$

$$B_a(x) = BM3D(x; a\hat{\sigma}) \quad (3.8)$$

The required anchor outputs are computed once per input image and reused during later evaluations. Interpolation avoids repeatedly running the most expensive denoising operator for every candidate control vector.

3.2.2 Homomorphic Illumination Correction

The logarithm of the denoised image is computed with a small offset to avoid taking the logarithm of zero.

$$\ell = \log(x_1 + 0.02) \quad (3.9)$$

$$L(\ell) = \mathcal{F}^{-1}[\text{Gof} \cdot \mathcal{R}(\ell)] \quad (3.10)$$

$$x_2 = \exp\{\ell - h[L(\ell) - \text{mean}(L(\ell))]\} \quad (3.11)$$

Here $\mathcal{F}$ and $\mathcal{F}^{-1}$ are the forward and inverse discrete Fourier transforms, Gof is the Gaussian low-pass transfer function, and $\sigma f = 0.02$ cycles per pixel. Parameter h controls the amount of estimated illumination removed.

3.2.3 DFT High-Frequency Emphasis and Stretching

$$H(D) = 1 + k[1 - \exp(-D^2 / (2D_0^2))] \quad (3.12)$$

$$x_3 = \mathcal{F}^{-1}[H(D) \cdot \mathcal{R}(x_2)] \quad (3.13)$$

D is the normalized radial frequency and $D_0 = 0.12$. The filtered result is robustly stretched between its 0.5th and 99.5th percentiles.

$$x_4 = S(x_3) = \text{clip}((x_3 - P_{0.5}(x_3)) / (P_{99.5}(x_3) - P_{0.5}(x_3)), 0, 1) \quad (3.14)$$

$P_q(\cdot)$ denotes the q th percentile. If the two percentile values coincide numerically, the implementation should use a small positive denominator floor to avoid division by zero.

3.2.4 CLAHE Blending and Gamma Mapping

$$y = [\alpha \cdot \text{CLAHEc}(x_4) + (1 - \alpha)x_4]^\gamma \quad (3.15)$$

$\text{CLAHEc}(\cdot)$ denotes contrast-limited adaptive histogram equalization with clip limit c on an 8×8 tile grid. The blend parameter $\alpha \in [0, 1]$ interpolates between the stretched image and the locally equalized image; γ controls final tonal mapping. The complete enhancement operator is denoted $y = E(x; u)$.

3.3 Modality-Aware Descriptor

The input image is represented by a 24-dimensional descriptor $\varphi(x)$, computed from the degraded image only. Its components cover intensity statistics, noise and contrast, structure, spectrum, texture, and spatial layout. Let the descriptor be:

$$\varphi(x) = [\varphi_1(x), \varphi_2(x), \dots, \varphi_{24}(x)]^T \in \mathbb{R}^{24} \quad (3.16)$$

The descriptor includes intensity mean, standard deviation, skewness, kurtosis, the 1st/50th/99th percentiles, histogram entropy, dark- and bright-pixel fractions; the wavelet noise estimate and Michelson contrast; mean Sobel gradient magnitude, Canny edge density, and Laplacian variance; low-, mid-, and high-frequency DFT power shares and log-log spectral slope; local standard deviation, standard deviation of local means over 16×16 blocks, grey-level co-occurrence contrast and homogeneity, and a stripe index.

$$H(I) = -\sum_b p_b \log p_b \quad (3.17)$$

$$C_m = (P_{95} - P_5) / (P_{95} + P_5) \quad (3.18)$$

$$\text{pstripe} = \log[(\text{std}(\text{column means}) + \varepsilon) / (\text{std}(\text{row means}) + \varepsilon)] \quad (3.19)$$

In (3.17), p_b is the normalized histogram probability for bin b . In (3.18), P_5 and P_{95} are the 5th and 95th intensity percentiles. In (3.19), $\varepsilon > 0$ prevents an undefined logarithm. The descriptor is computed without a reference image at inference time.

3.4 Unsupervised Domain Discovery

For the training set, descriptor components are standardized using training-set means and standard deviations. PCA then retains the smallest number of components explaining at least 95% of the variance.

$$z(\varphi) = [\varphi - \mu\varphi] \oslash (\sigma\varphi + \varepsilon) \quad (3.20)$$

$$v^* = \min\{v : (\sum_{i=1}^v \lambda_i) / (\sum_{i=1}^d \lambda_i) \geq 0.95\} \quad (3.21)$$

Here $\mu\varphi$ and $\sigma\varphi$ are the training descriptor mean and standard deviation, λ_i are PCA eigenvalues, $d = 24$, and $\oslash$ denotes element-wise division. K-means is fitted for each $K \in \{2, \dots, 12\}$; choose the K minimizing the Davies-Bouldin index.

$$K^* = \arg \min_{K \in \{2, \dots, 12\}} \text{DBI}(K) \quad (3.22)$$

For image x , let d_k be its squared distance to centroid k and $d_{\min} = \min_k d_k$. Soft domain membership is:

$$w_k(x) = \exp[-(d_k - d_{\min})/\tau] / \sum_{j=1}^{K^*} \exp[-(d_j - d_{\min})/\tau] \quad (3.23)$$

$$\tau = \text{median of nearest-centroid distances over the training set} \quad (3.24)$$

The membership vector $w(x) = [w_1(x), \dots, w_{K^*}(x)]^T$ sums to one and permits images near domain boundaries to draw information from multiple clusters.

3.5 Cluster-Balanced Multi-Domain Augmentation

Let n_c be the number of training images in domain c and $n_{\max} = \max_c n_c$. The number of additional samples drawn with replacement from domain c is:

$$m_c = \min(n_{\max} - n_c, n_c) \quad (3.25)$$

For each selected image, sample a dihedral transformation g from rotations by multiples of 90 degrees and optional horizontal/vertical flips. Apply the same geometric transform to the clean image and generate a new degradation using the degradation model.

$$x_o' = g(x_o); \quad x' = D(x_o'; \xi), \quad \xi \sim p(\xi | \text{domain } c) \quad (3.26)$$

Here x_o is the clean image, D is the degradation process, and ξ represents a fresh draw of degradation parameters/noise. Each synthetic pair (x', x_o') receives a newly computed oracle target. The cap $m_c \leq n_c$ prevents a domain from more than doubling through this augmentation step.

3.6 Random-Forest Quality Prediction and Parameter Selection

For each training pair (x, x_o) , the reference-guided oracle evaluates the fidelity of an enhanced output against its clean reference.

$$J(y, x_o) = \text{SSIM}(y, x_o) + 0.025 \cdot \text{PSNR}(y, x_o) \quad (3.27)$$

$$u^* = \arg \max_{u \in U_{\text{oracle}}} J(E(x; u), x_o) \quad (3.28)$$

The oracle candidate set is initialized with 24 Latin-hypercube candidates and a neutral setting, followed by 28 Gaussian perturbations around the incumbent with a shrinking search radius. This produces a reference-guided target u^* for training and an approximate upper bound for the selected search budget.

Rather than regressing u^* directly, HLMDE predicts the relative quality of a fixed bank of 82 candidates: 64 Latin-hypercube points and 18 structured anchors. The structured anchors vary denoising strength $s_w \in \{0.6, 1.0, 1.6\}$, gamma $\gamma \in \{0.8, 1.0, 1.25\}$, and CLAHE blend $\alpha \in \{0, 0.3\}$, with Fourier stages disabled.

$$B = \{b_1, b_2, \dots, b_{82}\} \quad (3.29)$$

$$J_{ij} = J(E(x_i; b_j), x_{o_i}) \quad (3.30)$$

$$q_{ij} = J_{ij} - (1/82) \sum_{j=1}^{82} J_{ij} \quad (3.31)$$

$$\hat{q}(x) = \text{fRF}([z(\varphi(x)), w(x)]) \in \mathbb{R}^{82} \quad (3.32)$$

$$j^* = \arg \max_j \hat{q}_j(x); \quad \hat{u}_o = b_{j^*} \quad (3.33)$$

The multi-output random forest uses 400 trees, minimum leaf size 2, and half of the available features considered at each split. The selected candidate is a coherent control vector already evaluated on training images. A direct-regression baseline instead fits the six components of u^* using the same forest configuration.

3.7 Reinforcement-Learning Refinement

Refinement is formulated as a finite-horizon Markov decision process (MDP). At each step, the state contains the standardized input descriptor, domain memberships, current normalized control vector, and seven descriptors of the current enhanced output.

$$s_t = [z(\varphi(x)), w(x), u_t, z(\varphi(y_t))] \quad (3.34)$$

The seven output descriptors are entropy, noise estimate, Michelson contrast, mean gradient magnitude, Laplacian variance, mean intensity, and standard deviation. The action space contains 12 parameter moves and a stop action.

$$A = \{+\delta e_i, -\delta e_i : i = 1, \dots, 6\} \cup \{\text{STOP}\}, \quad \delta = 0.15 \quad (3.35)$$

$$u' = \text{clip}(u_t + a, 0, 1) \quad \text{for } a \neq \text{STOP} \quad (3.36)$$

$$r_t = J(E(x; u'), x_o) - J(E(x; u_t), x_o) \quad (3.37)$$

The stop action is terminal and has reward zero. The episode horizon is $T = 4$ moves. Reference-based reward is available during training only; the learned policy is used at inference without access to x_o .

$$Q_{n+1} = \text{Fit}\{((s, a), r + \gamma \text{RL} \max_{a'} Q_n(s', a'))\} \quad (3.38)$$

$$\gamma \text{RL} = 0.8 \quad (3.39)$$

Fitted Q-iteration (FQI) is run for six iterations using an Extra-Trees regressor with 200 trees. The stop action contributes a value of zero. The trajectory starts from an out-of-fold random-forest prediction to approximate test-time prediction error. At each visited state, the 12 parameter moves are evaluated; the next state follows the best move with probability 0.7 and a random move otherwise.

$$a_t^* = \arg \max_{a \in A_{\text{move}}} Q(s_t, a) \quad (3.40)$$

$$\text{Stop if } \max_{a \in A_{\text{move}}} Q(s_t, a) \leq 0 \text{ or } t = T; \text{ otherwise apply } a_t^* \quad (3.41)$$

The learned Q-function serves as a reference-free quality critic at test time and determines whether another refinement move is predicted to improve quality.

3.8 Algorithm and Complexity

Algorithm 1. HLMDE inference with quality prediction and RL refinement

Input: degraded image x ; trained descriptor standardizer and PCA; K-means centroids; quality-prediction forest fRF; fitted Q-function Q ; horizon $T = 4$.

Output: enhanced image y and normalized control vector u .

1. Estimate $\hat{\sigma}$ from the finest diagonal wavelet subband.
2. Compute BM3D anchor outputs $B_a(x)$ for the anchors needed by candidate denoising strengths; reuse these outputs throughout inference.
3. Compute the 24-dimensional descriptor $\phi(x)$, standardize it, project it through the fitted PCA transform, and compute soft domain memberships $w(x)$.
4. Predict candidate qualities $\hat{q} = \text{fRF}([z(\phi(x)), w(x)])$.
5. Select $j^* = \arg \max_j \hat{q}_j(x)$; initialize $u \leftarrow b_{j^*}$ and $y \leftarrow E(x; u)$.
6. For $t = 1, \dots, T$:
 - a. Construct state $s_t = [z(\phi(x)), w(x), u, z(\phi(y))]$.
 - b. Evaluate $Q(s_t, a)$ for each of the 12 parameter-move actions.
 - c. If $\max_a Q(s_t, a) \leq 0$, terminate refinement.
 - d. Otherwise choose $a^* = \arg \max_a Q(s_t, a)$, update $u \leftarrow \text{clip}(u + a^*, 0, 1)$, and recompute $y \leftarrow E(x; u)$.
7. Return y and u .

Computational Complexity

Let N denote the number of image pixels, B the number of trees in the quality forest, and L the typical number of leaves per tree. The Fourier stages cost $O(N \log N)$ under

a conventional FFT implementation (or $O(N^2 \log N)$ under a direct 2-D indexing convention used in some image-size analyses); CLAHE costs $O(N)$. The source formulation characterizes the Fourier-stage cost as $O(N^2 \log N)$ and CLAHE as $O(N^2)$, so that convention is retained below.

$$C_{\text{chain}} = O(N^2 \log N) + O(N^2) = O(N^2 \log N) \quad (3.42)$$

$$C_{\text{forest}} = O(B \log L) \quad (3.43)$$

$$C_{\text{inference}} = C_{\text{descriptor}} + C_{\text{anchors}} + (1 + n_{\text{moves}})C_{\text{chain}} + C_{\text{forest}} \quad (3.44)$$

$$0 \leq n_{\text{moves}} \leq T = 4 \quad (3.45)$$

The dominant cost is BM3D anchor computation, performed once per input image and reused across chain evaluations. Inference performs one descriptor evaluation, at most three BM3D anchor computations (only the anchors required by the selected denoising strength), and one initial chain evaluation plus at most four refined evaluations. Forest prediction is negligible relative to image processing under the stated configuration.

4. Experimental Setup

4.1 Datasets

The benchmark contains 694 real images from seven modalities and six public sources (Table 2). Brain MRI slices come from the test partition of the brain-tumour classification collection of Bhuvaji et al. [48]. Chest radiographs and thoracic CT slices come from the COVID-19 image data collection [49]. Fundus photographs come from DRIVE [50] and CHASE_DB1 [51], using the green channel as is customary for retinal analysis. Satellite scenes are eight Landsat composites from 1985 to 2020 and aerial scenes are National Agriculture Imagery Program (NAIP) orthophotos, both distributed with the open geospatial data collection of [53]. Hyperspectral images are eight evenly spaced bands of the Pavia University, Salinas and Indian Pines cubes [52]. Colour images were converted to luminance, every image was centre-cropped or tiled to a square, resized to 256×256 pixels and normalised to $[0, 1]$ between its 0.5th and 99.5th percentiles.

Table 2. Benchmark composition. The split unit keeps all images of one patient, scene or acquisition on the same side of the 70/30 split.

Modality	Source	Train	Test	Split unit	Degradation model
MRI	Brain tumour MRI [48]	114	46	Image file	Contrast compression + Rician noise
CT	COVID-19 collection [49]	46	17	Patient	Contrast compression + Poisson–Gaussian noise
X-ray	COVID-19 collection [49]	113	46	Patient	Contrast compression + Poisson–Gaussian noise
Fundus	DRIVE [50], CHASE_DB1 [51]	46	22	Subject	Contrast compression + vignetting + Gaussian noise
Satellite	Landsat [53]	20	12	Scene year	Haze + Gaussian noise
Aerial	NAIP [53]	90	66	Acquisition	Haze + Gaussian noise
Hyperspectral	Pavia U., Salinas, Indian Pines [52]	32	24	Scene crop	Contrast compression + Gaussian + stripe noise
Total		461	233		

4.2 Physically motivated degradation

Full-reference evaluation needs a clean target, so each normalised image x_0 serves as the reference and a degraded version is synthesised with a model that matches the physics of its modality. All images first receive a mild Gaussian blur with σ drawn from $U(0, 0.8)$ pixels. Medical and hyperspectral images then undergo contrast compression $x = 1 + s \cdot x_0^g$ with $l \sim U(0.05, 0.3)$, $s \sim U(0.3, 0.6)$ and $g \sim U(0.7, 1.5)$, which mimics under-exposure and a poorly set display window. Satellite and aerial images instead pass through the atmospheric scattering model $x = t \cdot x_0 + A(1 - t)$ with transmission $t \sim U(0.5, 0.8)$ and airlight $A \sim U(0.7, 0.95)$ [34]. Modality-specific noise follows: Rician noise for MRI with $\sigma \sim U(0.02, 0.06)$ [42]; Poisson–Gaussian noise for CT and X-ray with photon count $N \sim U(150, 1200)$ and read noise $\sigma \sim U(0.005, 0.02)$ [43]; a radial illumination fall-off of depth $U(0.2, 0.5)$ around a random centre plus Gaussian noise for fundus; additive Gaussian plus column stripe noise for hyperspectral bands; and Gaussian noise with $\sigma \sim U(0.01, 0.04)$ for satellite and aerial images. On the test set the degraded images had a mean PSNR of 15.22 dB and a mean SSIM of 0.529 against their references, a demanding starting point.

4.3 Compared methods

Sixteen outputs were evaluated on every test image:

- Traditional: global histogram equalisation (HE); CLAHE with clip limit 0.01; wavelet BayesShrink followed by stretching and CLAHE (Wavelet+CLAHE); BM3D [9] with the estimated noise level followed by percentile stretching (BM3D+stretch).
- Fixed-parameter hybrids: the HLMDE chain with one control vector tuned for the mean objective over a stratified training subset (Global-tuned hybrid), and with one vector per modality chosen with the modality labels (Modality-LUT hybrid). Both use a 64-point Latin-hypercube grid over u .
- Learning-only: a multilayer-perceptron (MLP) denoiser in the style of Burger et al. [35] that maps an 11×11 patch plus three global percentiles to the clean centre pixel. It has two hidden layers of 256 and 128 units and was trained with Adam and early stopping on 200,000 patches from the training pairs.
- HLMDE ablations: direct regression of the control vector (on descriptors, and with domains and augmentation); candidate-quality selection on descriptors only, with domain memberships, and with domain memberships and augmentation; and the full framework with RL refinement.

- Oracle: the chain with the reference-guided control vector of each test image, and the best of the 82 bank candidates per image (bank oracle), two upper bounds on what a controller of this chain can achieve.

4.4 Evaluation metrics and statistics

Fidelity is measured by PSNR in dB and SSIM [45] against the reference. Two no-reference indicators describe the output itself: the Shannon entropy of the 256-bin histogram, which grows with the number of grey levels in use, and the measure of enhancement (EME) of Agaian et al. [46] on 8×8 blocks, which grows with local contrast. Because entropy and EME also reward amplified noise, they are reported as descriptive measures only, and conclusions rest on PSNR and SSIM. Paired differences between HLMDE and every other method are tested with the two-sided Wilcoxon signed-rank test [47] over the 233 test images.

4.5 Generalisation protocol

To measure cross-modality generalisation, a leave-one-modality-out (LOMO) study removes each modality in turn from every training stage (domain discovery, augmentation, oracle targets, regressor training and grid tuning) and evaluates on that modality's test images. The

RL refiner is excluded from LOMO because its logged transitions were collected with the full domain model, which would leak unlabelled information about the held-out modality.

4.6 Implementation

The framework is implemented in Python with NumPy, SciPy, scikit-image [55-59], PyWavelets and scikit-learn [54]; BM3D uses the reference bm3d package. All experiments ran on a two-core CPU without a GPU, with a fixed random seed (2026) for splitting, degradation, search and model fitting. Runtimes in Section 5 are single-threaded wall-clock times per 256×256 image.

5. Results and Discussion

5.1 Overall fidelity

HLMDE raised mean fidelity on the 233 test images from 15.22 dB / 0.529 SSIM to 26.44 dB / 0.813 SSIM, an 11.2 dB gain, and outperformed every traditional, fixed-parameter and learning-only method with $p < 10^{-20}$ (Table 3). The one exception is BM3D followed by percentile stretching, which HLMDE matched rather than beat (+0.04 dB, $p = 0.63$; +0.002 SSIM, $p = 0.14$).

Table 3. Mean $\pm$ standard deviation over 233 test images. Time is single-process wall-clock per 256×256 image, measured from scratch on 30 test images (— = not timed separately). Bold marks the best non-oracle value.

Method	PSNR (dB)	SSIM	Entropy (bits)	EME	Time (ms)
Degraded input	15.22 $\pm$ 3.10	0.529 $\pm$ 0.155	6.72	6.38	—
HE	15.09 $\pm$ 3.79	0.393 $\pm$ 0.186	8.00	19.05	4
CLAHE	15.10 $\pm$ 2.39	0.390 $\pm$ 0.184	7.72	15.05	6
Wavelet+CLAHE	17.91 $\pm$ 1.97	0.547 $\pm$ 0.131	7.74	12.80	10
BM3D+stretch	26.40 $\pm$ 4.22	0.811 $\pm$ 0.088	7.21	9.13	2,533
Global-tuned hybrid	21.82 $\pm$ 3.29	0.760 $\pm$ 0.104	7.06	11.00	5,008
Modality-LUT hybrid	22.79 $\pm$ 3.50	0.763 $\pm$ 0.105	7.04	10.05	—
Patch-MLP	23.64 $\pm$ 3.40	0.719 $\pm$ 0.112	7.32	13.69	1,403
HLMDE (full)	26.44 $\pm$ 4.32	0.813 $\pm$ 0.093	7.21	9.14	5,245
Oracle (continuous search)	28.22 $\pm$ 3.21	0.823 $\pm$ 0.082	7.19	9.93	—
Oracle (best of bank)	29.01 $\pm$ 3.07	0.835 $\pm$ 0.076	7.22	9.18	—

Three observations follow. First, contrast-only methods lose fidelity: HE and CLAHE produce the highest entropy and EME but the lowest SSIM, because they amplify the noise along with the structure; this is visible in the second column of Figure 2. The no-reference indices therefore reward exactly the artefact the framework is designed to avoid. Second, the patch MLP trained end-to-end on the same pairs stayed 2.8 dB and 0.095 SSIM behind HLMDE ($p < 10^{-21}$). It removed noise but left residual grain, and it cannot represent the global tone corrections a parameterised chain applies trivially. Third, BM3D with a robust stretch is a strong reference. It is the single best of the 82 bank candidates

on average, so an adaptive controller must learn when to deviate from it, which is harder than learning to approach it.

The fixed-parameter hybrids show why per-image control matters. A single vector tuned over all modalities (Global-tuned) reached only 21.82 dB, and even a per-modality look-up table chosen with labels reached 22.79 dB, 3.65 dB below HLMDE. The same operator chain therefore spans a range of more than 7 dB depending on how it is driven, and the oracles show a further 1.8–2.6 dB of headroom above HLMDE.

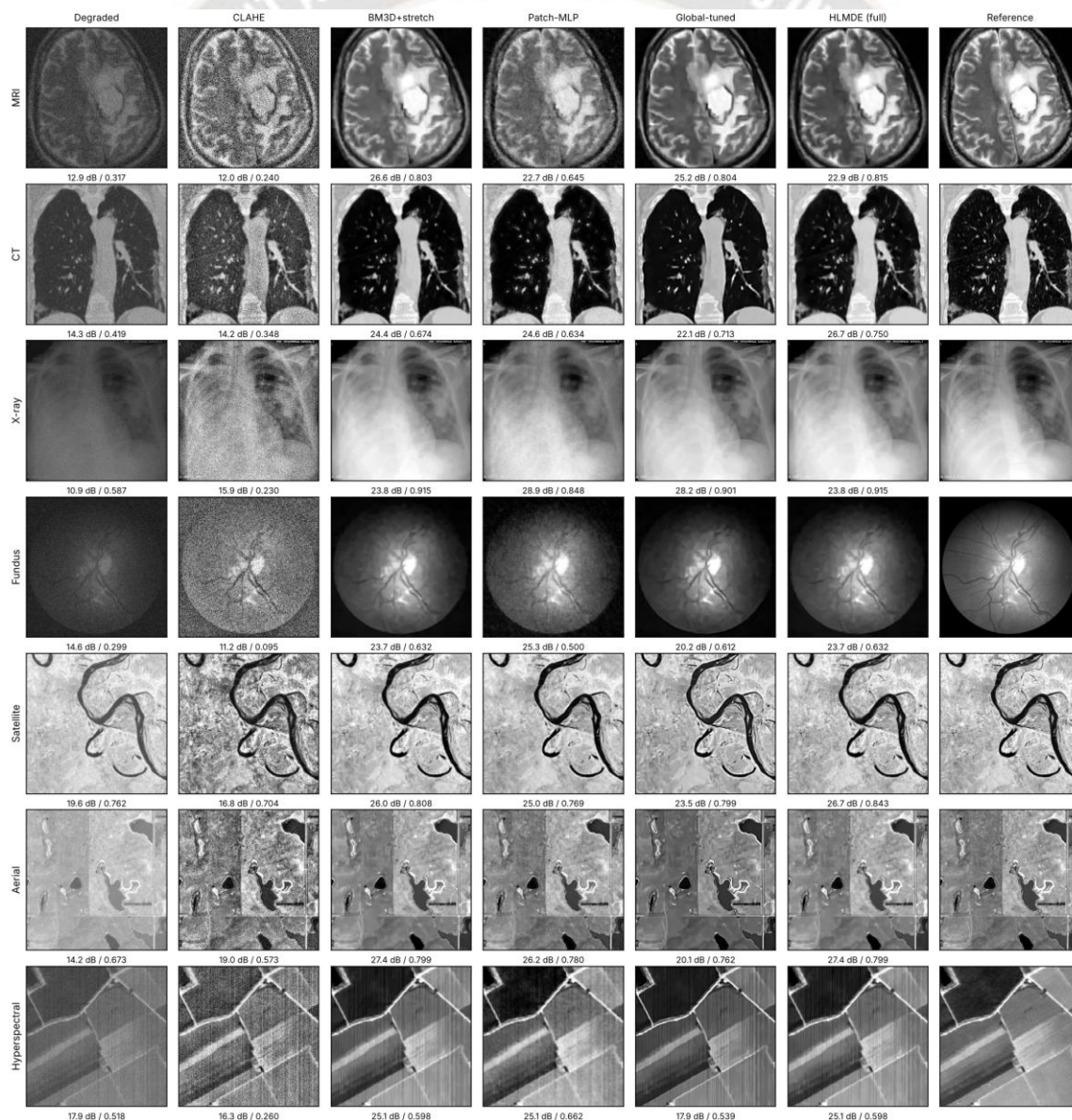


Figure 2. Representative test images (the image with the median HLMDE gain in each modality, not hand-picked). Values under each panel are PSNR / SSIM against the reference.

5.2 Per-modality behaviour

Gains were not uniform across modalities (Figure 3). The largest advantage over BM3D+stretch appeared for Landsat imagery (29.01 vs 27.50 dB), where the controller learned to halve the denoising strength (mean $s_w = 0.51$) and thereby kept fine terrain texture that the default noise estimate would have smoothed away. CT (+0.62 dB) and hyperspectral bands (+0.45 dB) also benefited. HLMDE was slightly worse than BM3D+stretch on fundus images (−0.81 dB) and MRI (−0.31 dB). In both cases the bank oracle is about 3.5 dB higher, which shows that a better control vector existed but the quality predictor did not identify it from the descriptor.

5.3 Ablation study

Table 4 isolates each learning component. All variants share the operator chain, the descriptor and the training data.

Table 4. Ablation on the test set. Δ and p compare each row with the row above it (two-sided Wilcoxon signed-rank test, $n = 233$); the first selection row is compared with direct regression on descriptors.

Variant	PSNR (dB)	SSIM	Δ PSNR (p)	Δ SSIM (p)
RF regression, descriptors	25.54	0.801	—	—
RF regression + domains + augmentation	25.62	0.801	—	—
RF selection, descriptors	26.58	0.816	+1.05 (2.2×10^{-6})	+0.015 (3.5×10^{-7})
+ domain memberships	26.56	0.817	−0.02 (0.97)	+0.002 (0.31)
+ cluster-balanced augmentation	26.42	0.813	−0.15 (0.20)	−0.004 (0.044)
+ RL refinement (HLMDE full)	26.44	0.813	+0.02 (0.12)	<0.001 (0.52)

The decisive component is the change from regressing parameters to predicting candidate quality: +1.05 dB and +0.015 SSIM, both highly significant, confirming that averaging control vectors across a multimodal landscape is harmful. Domain memberships did not change PSNR but produced the highest SSIM of all non-oracle variants (0.817); against BM3D+stretch this variant gained +0.006 SSIM ($p = 0.006$) and +0.17 dB ($p = 0.39$). Cluster-balanced augmentation slightly reduced SSIM ($p = 0.044$). A plausible cause is that the synthetic pairs are rotated and flipped copies of the same scenes, so they add little new information while shifting the forest towards small domains. RL refinement never chose to stop, yet it improved the result on only 4.7% of images, with no significant net effect. A trace of 60 test images explains why: 87% of the selected moves pushed a parameter that

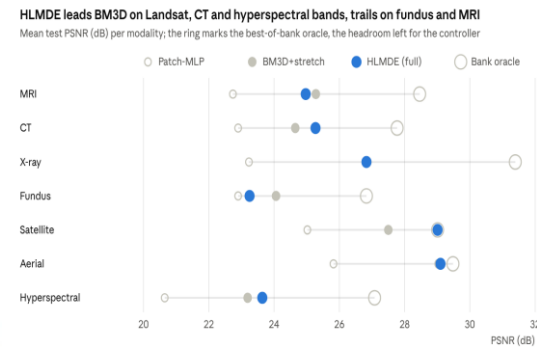


Figure 3 · test-set PSNR by modality, 233 images

Figure 3. Mean test PSNR by modality for the learning-only baseline, BM3D+stretch, HLMDE and the best-of-bank oracle.

was already at its bound (for example lowering a high-frequency gain that was already zero), so they changed nothing, and the final vector differed from its start in only 12 of the 60 images. The Q-function thus learned that small positive values are attainable but not which moves realise them. Masking infeasible moves, a finer step than $\delta = 0.15$, more than 461 training trajectories and a learned stop threshold are direct remedies.

5.4 Discovered domains and what the controller learned

The Davies–Bouldin index was minimised at $K = 9$ domains in a 9-dimensional PCA space. These domains align only partly with modality (normalised mutual information 0.39, adjusted Rand index 0.27). One domain grouped 58 radiographs with 9 CT slices and 6 fundus images; another combined 49 aerial tiles with 10

CT and 9 MRI slices; and MRI images were spread mainly over three domains (50, 30 and 10 images). Enhancement-relevant appearance therefore cuts across acquisition modality, which supports learning domains from the data rather than hard-coding them.

The learned control vectors (Table 5) are physically sensible. Denoising stayed near the noise estimate for medical images and was halved for Landsat scenes;

gamma fell below 1 for CT and radiographs, brightening the compressed low end of the range, and stayed near 1 elsewhere. The homomorphic and high-frequency stages were switched off for almost all images, and the CLAHE blend stayed below 0.05. Under a fidelity objective, any operator that adds contrast the reference does not have is penalised. These stages would matter under perceptual or task-driven objectives, which the framework supports by changing J.

Table 5. Mean HLMDE control vector by modality on the test set.

Modality	Denoise scale s_w	HF gain k	Homomorphi c_h	CLAHE clip c	CLAHE blend α	Gamma γ
MRI	1.03	0.00	0.00	0.0080	0.05	1.04
CT	1.00	0.00	0.00	0.0092	0.00	0.94
X-ray	1.00	0.00	0.00	0.0086	0.00	0.94
Fundus	1.00	0.00	0.00	0.0069	0.04	1.03
Satellite	0.51	0.00	0.00	0.0115	0.00	1.00
Aerial	1.00	0.02	0.00	0.0071	0.00	1.00
Hyperspectral	1.00	0.00	0.00	0.0072	0.04	0.97

Random-forest importances in the direct-regression variant point to the same physics. The denoising strength was driven mainly by the 99th intensity percentile (importance 0.26) and mid-band spectral energy (0.10); homomorphic strength by the illumination non-uniformity index (0.14); high-frequency gain by Michelson contrast (0.11); and the CLAHE clip limit by the 99th percentile (0.15).

5.5 Cross-modality generalisation

When a modality was removed from all training stages, the learned selector lost on average 0.75 dB across the

seven held-out modalities compared with in-distribution training (25.24 vs 25.99 dB). The end-to-end MLP lost 2.14 dB (21.18 vs 23.32 dB), almost three times as much (Table 6). Because the selector only chooses among operator settings, it cannot produce the texture hallucinations or tone shifts that an unseen domain induces in a pixel-level model. On held-out hyperspectral bands it even exceeded BM3D+stretch (23.61 vs 23.19 dB); on Landsat it fell back exactly to the BM3D setting, a safe default.

Table 6. Leave-one-modality-out PSNR (dB) / SSIM on each held-out modality. CLAHE and BM3D+stretch need no training and are repeated for reference.

Held-out modality	CLAHE	Global-tuned hybrid	Patch-MLP	BM3D+stretch	HLMDE selector
MRI	12.98 / 0.288	22.09 / 0.646	20.58 / 0.556	25.28 / 0.767	23.44 / 0.719
CT	14.60 / 0.457	18.98 / 0.716	22.13 / 0.658	24.65 / 0.764	24.21 / 0.755
X-ray	14.55 / 0.265	21.50 / 0.829	20.39 / 0.707	26.86 / 0.862	25.93 / 0.852
Fundus	14.50 / 0.211	22.42 / 0.686	20.47 / 0.611	24.06 / 0.771	23.36 / 0.762

Satellite	16.12 / 0.673	22.85 / 0.779	23.98 / 0.758	27.50 / 0.805	27.50 / 0.805
Aerial	17.51 / 0.582	22.57 / 0.832	20.23 / 0.753	29.04 / 0.871	28.66 / 0.869
Hyperspectral	14.02 / 0.269	21.51 / 0.681	20.49 / 0.615	23.19 / 0.707	23.61 / 0.707

HLMDE needed 5.2 s per image on one CPU process, against 2.5 s for BM3D+stretch, 1.4 s for the MLP and a few milliseconds for HE and CLAHE (Table 3). The cost is dominated by the BM3D anchors, about 2.5 s each, of which one or two are needed per image. The descriptor, forest prediction and light chain evaluations together cost well under 0.5 s, and RL refinement adds about 0.3 s. A GPU or fast approximate BM3D, or computing a single anchor when the predicted s_w falls exactly on one, would bring the framework close to the cost of its denoiser.

The results support three conclusions. First, learning how to drive classical operators is an effective and safe alternative to learning the pixel mapping. With a CPU-only random forest and 461 training images, HLMDE outperformed an end-to-end learned denoiser by 2.8 dB and generalised to unseen modalities with about a third of its loss. Second, how the controller is learned matters more than its inputs: predicting the quality of a candidate bank instead of regressing parameters accounted for most of the gain, while domain memberships, augmentation and RL refinement contributed little on this benchmark. Third, a well-configured transform-domain denoiser is a demanding baseline that much of the enhancement literature omits. HLMDE recovers it automatically and improves on it where the data justify a deviation (remote sensing, CT, hyperspectral). The 2.6 dB gap to the bank oracle marks the main opportunity: a better quality predictor, for example one using richer descriptors or a small learned critic, would translate directly into fidelity because the bank already contains the better settings.

6. Conclusion

This paper presented HLMDE, a hybrid learning-based framework that enhances images from heterogeneous medical and environmental modalities by learning to control a transparent chain of transform-domain, Fourier and histogram operators rather than learning pixels. On 694 real images from seven modalities it raised fidelity by 11.2 dB over the degraded input, outperformed classical contrast enhancement, fixed-parameter hybrids and an end-to-end learned denoiser, and matched a strong BM3D baseline overall while exceeding it on satellite,

CT and hyperspectral data. The ablation identified predicting the quality of candidate parameter vectors, rather than regressing the parameters, as the key design choice (+1.05 dB). Unsupervised domain memberships gave the best structural similarity, while cluster-balanced augmentation and fitted-Q-iteration refinement brought no significant gain in their present form. Under cross-modality shift the learned controller degraded about three times less than a pixel-level network, and every output carries an explicit parameter record that can be audited.

Future work will (i) close the 2.6 dB gap to the bank oracle with stronger quality predictors and feasibility-aware RL actions, (ii) replace synthetic degradations with paired clinical and remote-sensing acquisitions and reader studies, (iii) add operators for structured artefacts such as streaks and speckle, and (iv) train the controller across institutions without sharing data.

References

1. R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 4th ed. New York, NY, USA: Pearson, 2018.
2. S. M. Pizer et al., "Adaptive histogram equalization and its variations," *Computer Vision, Graphics, and Image Processing*, vol. 39, no. 3, pp. 355–368, 1987.
3. K. Zuiderveld, "Contrast limited adaptive histogram equalization," in *Graphics Gems IV*, P. S. Heckbert, Ed. San Diego, CA, USA: Academic Press, 1994, pp. 474–485.
4. E. D. Pisano et al., "Contrast limited adaptive histogram equalization image processing to improve the detection of simulated spiculations in dense mammograms," *Journal of Digital Imaging*, vol. 11, no. 4, pp. 193–200, 1998.
5. S. G. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 7, pp. 674–693, 1989.
6. D. L. Donoho, "De-noising by soft-thresholding," *IEEE Transactions on*

- Information Theory, vol. 41, no. 3, pp. 613–627, 1995.
7. S. G. Chang, B. Yu, and M. Vetterli, "Adaptive wavelet thresholding for image denoising and compression," *IEEE Transactions on Image Processing*, vol. 9, no. 9, pp. 1532–1546, 2000.
 8. V. Oppenheim, R. W. Schafer, and T. G. Stockham, "Nonlinear filtering of multiplied and convolved signals," *Proceedings of the IEEE*, vol. 56, no. 8, pp. 1264–1291, 1968.
 9. K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative filtering," *IEEE Transactions on Image Processing*, vol. 16, no. 8, pp. 2080–2095, 2007.
 10. K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising," *IEEE Transactions on Image Processing*, vol. 26, no. 7, pp. 3142–3155, 2017.
 11. C. Ledig et al., "Photo-realistic single image super-resolution using a generative adversarial network," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 4681–4690.
 12. J. Liang, J. Cao, G. Sun, K. Zhang, L. Van Gool, and R. Timofte, "SwinIR: Image restoration using Swin transformer," in *Proc. IEEE/CVF Int. Conf. Computer Vision Workshops (ICCVW)*, 2021, pp. 1833–1844.
 13. S. W. Zamir, A. Arora, S. Khan, M. Hayat, F. S. Khan, and M.-H. Yang, "Restormer: Efficient transformer for high-resolution image restoration," in *Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR)*, 2022, pp. 5728–5739.
 14. B. Rakshit, R. Das, and N. Chattaraj, "Detection-accuracy enhancement of COVID-19 from multi-class lung diseases by instrumenting CLAHE integrated deep learning technique," in *Proc. 2022 IEEE 2nd Int. Symp. Sustainable Energy, Signal Processing and Cyber Security (iSSSC)*, 2022, pp. 1–6.
 15. C. Wang et al., "GCT-VAE-GAN: An image enhancement network for low-light cattle farm scenes by integrating fusion gate transformation mechanism and variational autoencoder GAN," *IEEE Access*, vol. 11, pp. 126650–126660, 2023.
 16. Rouhbakhshmeghraz, B. Li, S. Nalbandian, C. Song, G. Alizadeh, and M. R. Hassannezhad, "SRGAN enhancement through autoencoder-pretrained U-Net with residual blocks for improved image super-resolution," *Modeling and Simulation in Electrical and Electronics Engineering*, vol. 4, no. 3, pp. 11–24, 2025.
 17. S. C. Tai, T. C. Tsai, and J. H. Huang, "Underwater image enhancement through depth estimation based on random forest," *Journal of Electronic Imaging*, vol. 26, no. 6, p. 063026, 2017.
 18. C. Prabhakar, H. Li, J. Yang, S. Shit, B. Wiestler, and B. Menze, "ViT-AE++: Improving vision transformer autoencoder for self-supervised medical image representations," in *Proc. Medical Imaging with Deep Learning (MIDL)*, PMLR, 2024, pp. 666–679.
 19. Y. Kim and W. Lee, "Distributed Raman spectrum data augmentation system using federated learning with deep generative models," *Sensors*, vol. 22, no. 24, p. 9900, 2022.
 20. K. Jiang, Q. Wang, Z. An, Z. Wang, C. Zhang, and C.-W. Lin, "Mutual Retinex: Combining transformer and CNN for image enhancement," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 8, no. 3, pp. 2240–2252, 2024.
 21. H. Guan and M. Liu, "Domain adaptation for medical image analysis: A survey," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 3, pp. 1173–1185, 2022.
 22. K. Zhou, Z. Liu, Y. Qiao, T. Xiang, and C. C. Loy, "Domain generalization: A survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 4, pp. 4396–4415, 2023.
 23. G. F. C. Campos et al., "Machine learning hyperparameter selection for contrast limited adaptive histogram equalization," *EURASIP Journal on Image and Video Processing*, vol. 2019, art. 59, 2019, [doi:10.1186/s13640-019-0445-4](https://doi.org/10.1186/s13640-019-0445-4).
 24. J. Park, J.-Y. Lee, D. Yoo, and I. S. Kweon, "Distort-and-recover: Color enhancement using deep reinforcement learning," in *Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR)*, 2018, pp. 5928–5936.
 25. K. Yu, C. Dong, L. Lin, and C. C. Loy, "Crafting a toolchain for image restoration by

- deep reinforcement learning," in Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR), 2018, pp. 2443–2452.
26. R. Furuta, N. Inoue, and T. Yamasaki, "Fully convolutional network with multi-step reinforcement learning for image processing," in Proc. AAAI Conf. Artificial Intelligence, vol. 33, no. 1, 2019, pp. 3598–3605, [AAAI](#).
27. D. Ernst, P. Geurts, and L. Wehenkel, "Tree-based batch mode reinforcement learning," *Journal of Machine Learning Research*, vol. 6, pp. 503–556, 2005.
28. L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.
29. P. Geurts, D. Ernst, and L. Wehenkel, "Extremely randomized trees," *Machine Learning*, vol. 63, no. 1, pp. 3–42, 2006.
30. M. Reza, "Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement," *Journal of VLSI Signal Processing Systems*, vol. 38, no. 1, pp. 35–44, 2004.
31. J. A. Stark, "Adaptive image contrast enhancement using generalizations of histogram equalization," *IEEE Transactions on Image Processing*, vol. 9, no. 5, pp. 889–896, 2000.
32. X. Guo, Y. Li, and H. Ling, "LIME: Low-light image enhancement via illumination map estimation," *IEEE Transactions on Image Processing*, vol. 26, no. 2, pp. 982–993, 2017.
33. C. Wei, W. Wang, W. Yang, and J. Liu, "Deep Retinex decomposition for low-light enhancement," in Proc. British Machine Vision Conference (BMVC), 2018.
34. K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 12, pp. 2341–2353, 2011.
35. H. C. Burger, C. J. Schuler, and S. Harmeling, "Image denoising: Can plain neural networks compete with BM3D?" in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2012, pp. 2392–2399.
36. C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *Journal of Big Data*, vol. 6, art. 60, 2019.
37. S. P. Lloyd, "Least squares quantization in PCM," *IEEE Transactions on Information Theory*, vol. 28, no. 2, pp. 129–137, 1982.
38. T. Jolliffe and J. Cadima, "Principal component analysis: A review and recent developments," *Philosophical Transactions of the Royal Society A*, vol. 374, no. 2065, art. 20150202, 2016.
39. D. L. Davies and D. W. Bouldin, "A cluster separation measure," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-1, no. 2, pp. 224–227, 1979.
40. R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-3, no. 6, pp. 610–621, 1973.
41. D. L. Donoho and I. M. Johnstone, "Ideal spatial adaptation by wavelet shrinkage," *Biometrika*, vol. 81, no. 3, pp. 425–455, 1994.
42. H. Gudbjartsson and S. Patz, "The Rician distribution of noisy MRI data," *Magnetic Resonance in Medicine*, vol. 34, no. 6, pp. 910–914, 1995.
43. Foi, M. Trimeche, V. Katkovnik, and K. Egiazarian, "Practical Poissonian-Gaussian noise modeling and fitting for single-image raw-data," *IEEE Transactions on Image Processing*, vol. 17, no. 10, pp. 1737–1754, 2008.
44. R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*, 2nd ed. Cambridge, MA, USA: MIT Press, 2018.
45. Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, 2004.
46. S. S. Agaian, K. Panetta, and A. M. Grigoryan, "Transform-based image enhancement algorithms with performance measure," *IEEE Transactions on Image Processing*, vol. 10, no. 3, pp. 367–382, 2001.
47. F. Wilcoxon, "Individual comparisons by ranking methods," *Biometrics Bulletin*, vol. 1, no. 6, pp. 80–83, 1945.
48. S. Bhuvaji, A. Kadam, P. Bhumkar, S. Dedge, and S. Kanchan, "Brain tumor classification (MRI) dataset," 2020. [Online]. Available: github.com/sartajbhuvaji/brain-tumor-classification-dataset

49. P. Cohen, P. Morrison, L. Dao, K. Roth, T. Q. Duong, and M. Ghassemi, "COVID-19 image data collection: Prospective predictions are the future," *Machine Learning for Biomedical Imaging*, vol. 1, pp. 1–38, 2020. Data: github.com/ieee8023/covid-chestxray-dataset
50. Staal, M. D. Abràmoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken, "Ridge-based vessel segmentation in color images of the retina," *IEEE Transactions on Medical Imaging*, vol. 23, no. 4, pp. 501–509, 2004.
51. M. Fraz et al., "An ensemble classification-based approach applied to retinal blood vessel segmentation," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 9, pp. 2538–2548, 2012.
52. S. K. Roy, G. Krishna, S. R. Dubey, and B. B. Chaudhuri, "HybridSN: Exploring 3-D-2-D CNN feature hierarchy for hyperspectral image classification," *IEEE Geoscience and Remote Sensing Letters*, vol. 17, no. 2, pp. 277–281, 2020. Data: github.com/gokriznastic/HybridSN
53. Q. Wu, "geemap: A Python package for interactive mapping with Google Earth Engine," *Journal of Open Source Software*, vol. 5, no. 51, p. 2305, 2020. Data: github.com/opengeos/data
54. F. Pedregosa et al., "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
55. S. van der Walt et al., "scikit-image: Image processing in Python," *PeerJ*, vol. 2, p. e453, 2014.
56. Mittal, R. Soundararajan, and A. C. Bovik, "Making a 'completely blind' image quality analyzer," *IEEE Signal Processing Letters*, vol. 20, no. 3, pp. 209–212, 2013.
57. George Zacharia "Agentic AI for Autonomous Cloud Infrastructure Management: A Multi-Agent Framework for Fault Detection, Root-Cause Analysis, and Self-Healing," *Journal of Cyber-Physical Security and Robotics*, vol. 2, no. 1, pp. 63–76, 2026, doi: 10.64235/r8ves107.
58. R. Pothu and G. Zacharia, "AI-Driven Cyber Threat Intelligence for Predictive Attack Detection and Automated Security Response", *IJAIML*, vol. 6, no. 12s, pp. 1–9, Sep. 2026.
59. G. Zacharia, "A verification-centred framework for generative AI-assisted code generation, testing, and developer productivity," *Quantum Pulse: Journal of AI, Data Science & Systems Engineering*, vol. 2, no. 2, 2026.