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A Hybrid PNet and U-Net Autoencoder Framework for High-Fidelity Medical Image Super-Resolution

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Abstract: High-resolution (HR) medical imaging is critical for accurate clinical diagnosis and computer-aided analysis. However, acquiring HR images is often limited by hardware constraints, acquisition time, and patient safety concerns regarding radiation exposure. Single Image Super-Resolution (SISR) has emerged as a post-processing solution, yet traditional convolutional neural networks (CNNs) often struggle to preserve high-frequency diagnostic details, resulting in over-smoothed textures [4]. This paper proposes a novel deep learning framework that integrates a Pyramid Network (PNet) into U-Net based autoencoder architecture to address these limitations. The proposed model leverages the symmetric encoder-decoder structure of the U-Net for efficient feature reconstruction while embedding a PNet module at the bottleneck to capture multi-scale contextual information. This hybrid approach allows the network to dynamically aggregate features from different receptive fields, effectively recovering both global anatomical structures and local tissue textures. Furthermore, a residual learning [8] strategy is employed to accelerate convergence and allow the network to focus on learning high-frequency residuals rather than the direct image mapping. Extensive experiments were conducted on the BraTS 2020 and DeepLesion dataset. Quantitative evaluations demonstrate that the proposed Hybrid PNet-UNet outperforms state-of-the-art methods, achieving a Peak Signal-to-Noise Ratio (PSNR) of 31.45 dB and a Structural Similarity Index (SSIM) of 0.9246. Visual results confirm that the model significantly reduces blurring artifacts and enhances edge definition, making it a promising tool for improving diagnostic precision in medical imaging.

Keywords: *Medical Image Super-Resolution, U-Net, Pyramid Networks (PNet), Autoencoder, Deep Learning, Multi-scale Feature Extraction.*

1. Introduction

Medical imaging has firmly established itself as an indispensable pillar of modern healthcare, facilitating non-invasive diagnosis, treatment planning, and image-guided surgery. Modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Ultrasound provide clinicians with crucial anatomical and functional information [1-3] that determines patient outcomes. In this context, the spatial resolution of an image is paramount [10]; high-resolution (HR) images offer finer details, sharper edges, and clearer texture definitions, which are essential for the early detection of subtle pathologies such as micro-lesions, small tumours, or vascular anomalies.

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However, the acquisition of high-resolution medical images is frequently hindered by inherent hardware limitations and safety constraints. In MRI, increasing spatial resolution typically requires longer acquisition times, which not only reduces patient throughput but also increases the likelihood of motion artifacts due to patient discomfort [1]. In X-ray and CT imaging, higher resolution often necessitates a higher radiation dose, posing significant long-term health risks to patients [5]. Consequently, clinical protocols often settle for Low-Resolution (LR) scans to balance image quality with acquisition speed and patient safety. This trade-off creates a significant demand for post-processing techniques capable of computationally enhancing LR images to HR quality—a process known as Single Image Super-Resolution (SISR) [8].

Historically, image super-resolution was approached using interpolation-based methods such as nearest-neighbour, bilinear, and bicubic interpolation [4]. While these techniques are computationally efficient, they operate on local pixel neighbourhoods without learning high-frequency semantic information. As a result, interpolated medical images often suffer from blurring and aliasing artifacts, failing to recover the high-frequency details required for precise medical diagnosis.

The advent of Deep Learning (DL) has revolutionized the field of SISR [6-8]. Early Convolutional Neural Networks (CNNs), such as the Super-Resolution CNN (SRCNN), demonstrated the ability to learn complex mappings from LR to HR spaces, significantly outperforming traditional interpolation. These models treat SR as a regression problem, learning to predict missing pixel information based on vast datasets of training examples. Despite their success, standard CNN architectures often struggle with the complex, non-Euclidean structures found in medical anatomy. They tend to rely on local receptive fields, which may fail to capture the global context necessary to distinguish between anatomical noise and actual tissue texture.

To address the need for structural understanding, the U-Net architecture emerged as a dominant force in medical image analysis[13]. Originally designed for biomedical image segmentation, the U-Net is characterized by its symmetric encoder-decoder structure and skip connections. The encoder path compresses the input image into a latent feature representation, capturing the global context, while the decoder path reconstructs the spatial dimensions. The skip connections are the architecture's defining feature; they shuttle high-resolution features from the encoder directly to the decoder, preventing the loss of fine spatial information during down sampling.

While U-Net has achieved state-of-the-art results in segmentation, its direct application to Super-Resolution presents unique challenges. Super-resolution requires not just the localization of features (as in segmentation) but the synthesis of plausible texture and detail that does not exist in the input [14]. A standard U-Net, with its fixed receptive field at each layer, may struggle to handle the multi-scale variations inherent in biological tissues. For instance, a lesion may appear as a large, distinct object or a tiny, subtle texture irregularity. A network with a fixed scale may over-smooth these fine details or fail to recognize large-scale structural coherency, leading to "hallucinations" or artifacts in the reconstructed image.

1.1 The Need for Multi-Scale Feature Extraction: The PNet

This limitation brings us to the concept of Pyramid Networks (PNets). In computer vision, pyramid structures—such as Spatial Pyramid Pooling (SPP) or Atrous Spatial Pyramid Pooling (ASPP)—are designed to overcome the constraints of fixed receptive fields. By processing feature maps at multiple scales (or dilation rates) simultaneously, PNets can capture fine details and global context in parallel.

In the context of super-resolution, a Pyramid Network allows the model to "see" the image through different lenses: one lens focuses on minute textures, while another focuses on the overall shape of the organ. Integrating this capability into an autoencoder is crucial for medical imaging, where the diagnostic value lies in the simultaneous preservation of organ boundaries (global) and tissue micro-structures (local).

This research proposes a novel **Hybrid PNet and U-Net Model**, a unified autoencoder framework specifically engineered for medical image super-resolution. This architecture synergizes the reconstruction power of the U-Net with the multi-scale feature extraction capabilities of the PNet.

In our proposed design, the U-Net serves as the backbone, providing the necessary encoder-decoder pathway for effectively mapping LR inputs to HR outputs. To enhance this backbone, we integrate a Pyramid module at the bottleneck [13, 17] (the deepest part of the network). This placement allows the network to enrich the latent representation with multi-scale context before the reconstruction phase begins. Furthermore, we employ a residual learning strategy, where the network learns to predict the high-frequency residual map (the difference between the HR and LR images) rather than the HR image itself. This approach significantly stabilizes training and ensures that the model focuses its computational capacity on recovering the missing high-frequency details rather than relearning the low-frequency base image.

The primary contributions of this paper are summarized as follows:

1. **Novel Hybrid Architecture:** We introduce a customized autoencoder that embeds a Pyramid Network module within a U-Net backbone. This design effectively mitigates the limitations of fixed receptive fields, allowing for robust super-resolution across varying anatomical scales.
2. **Enhanced Detail Recovery:** By combining skip connections with multi-scale pooling, our model demonstrates superior capability in recovering high-frequency textures and edge information compared to standard CNN and vanilla U-Net approaches.
3. **Medical-Specific Optimization:** The model is optimized for medical imaging modalities, prioritizing the preservation of structural fidelity and the minimization of hallucinated artifacts, which are critical for clinical reliability.
4. **Comprehensive Evaluation:** We provide a rigorous comparative analysis against state-of-the-art SR methods using quantitative metrics (PSNR, SSIM) and qualitative visual assessments on benchmark medical datasets.

The remainder of this paper is organized as follows: Section 2 reviews related work in deep learning-based super-resolution and medical image analysis. Section 3 details the methodology, explaining the architectural design of the Hybrid PNet and U-Net model and the loss functions employed. Section 4 presents the experimental setup, including dataset descriptions and training protocols. Section 5 provides a comprehensive analysis of the results and comparisons with existing methods. finally, Section 6 concludes the paper and outlines future research directions.

2. Related Work

The pursuit of High-Resolution (HR) medical imaging through computational means has evolved significantly over the past decade. This section reviews the trajectory of Single Image Super-Resolution (SISR) techniques, focusing on the transition from traditional interpolation to advanced deep learning architectures. Specifically, we examine the foundational role of Convolutional Neural Networks (CNNs), the ubiquity of U-Net in medical analysis, and the integration of Pyramid Networks for multi-scale feature extraction.

2.1 Deep Learning Approaches for Single Image Super-Resolution

The field of SISR witnessed a paradigm shift with the introduction of deep learning. Prior to this, reconstruction relied heavily on example-based learning or interpolation methods (bicubic, varying splines), which fundamentally lacked the capacity to hallucinate high-frequency textures missing from Low-Resolution (LR) inputs [3,4].

Convolutional Neural Networks (CNNs): The seminal work by Dong et al. introduced the Super-Resolution Convolutional Neural Network (SRCNN). This three-layer architecture successfully demonstrated that a neural network could learn an end-to-end mapping between LR and HR images, significantly outperforming bicubic interpolation in terms of Peak Signal-to-Noise Ratio (PSNR). SRCNN treated super-resolution as a regression problem, but its shallow depth limited its ability to capture complex hierarchical features.

Building on this, Kim et al. proposed the Very Deep Super-Resolution (VDSR) network. VDSR addressed the vanishing gradient problem in deeper networks by introducing global residual learning. By forcing the network to learn only the high-frequency residual component (the difference between the input and target) rather than the full image, VDSR achieved faster convergence and superior accuracy [19, 22].

Generative Adversarial Networks (GANs): While CNNs optimized for Mean Squared Error (MSE) achieved high PSNR scores, they often produced perceptually smooth or blurry textures. To address this "regression-to-the-mean" problem, Ledig et al. introduced SRGAN (Super-Resolution Generative Adversarial Network). SRGAN employed a perceptual loss function [17] and an adversarial discriminator, driving the generator to create photo-realistic textures. While highly effective for natural images, GANs pose specific risks in medical imaging due to their tendency to generate artifacts or "hallucinate" anatomical details that do not exist, necessitating careful validation in clinical contexts.

2.2 U-Net Architectures in Medical Image Analysis

In the domain of medical imaging, the U-Net architecture, proposed by Ronneberger et al. in 2015, represents a cornerstone development. Originally designed for biomedical image segmentation (e.g., cell tracking), the U-Net is an Encoder-Decoder network characterized by its symmetric shape and skip connections.

The Encoder-Decoder Mechanism: The contracting path (encoder) captures context by progressively down sampling the spatial dimensions while increasing feature channels. Conversely, the expanding path (decoder) enables precise localization by up sampling the feature maps. This structure is inherently suited for "image-to-image" translation tasks, making it a natural candidate for super-resolution and denoising, not just segmentation.

Adaptation for Super-Resolution: Researchers quickly adapted U-Net for restoration tasks. For instance, in MRI reconstruction, U-Net variants have been used to map under sampled k-space data to fully sampled images [33]. The skip connections play a critical role here; by shuttling low-level feature maps (edges, gradients) directly from the encoder to the decoder, the network preserves the spatial fidelity that is often lost during the down sampling process of standard autoencoders [24]. However, a standard U-Net typically utilizes fixed-size convolution kernels (e.g., 3×3), which limits the network's effective receptive field. This limitation can be problematic when dealing with medical pathologies that vary drastically in size, such as varying tumour diameters or diverse vessel thicknesses in retinal scans.

2.3 Pyramid Networks and Multi-Scale Feature Extraction

To overcome the limitation of fixed receptive fields, the computer vision community developed multi-scale feature extraction techniques, prominently featured in Pyramid Networks.

Spatial Pyramid Pooling (SPP): He et al. introduced Spatial Pyramid Pooling to allow networks to generate a fixed-length representation regardless of input size. This concept evolved into the Atrous Spatial Pyramid Pooling (ASPP) module used in the DeepLab series for semantic segmentation [10]. ASPP employs multiple parallel convolutional filters with different dilation rates. This allows the network to sample the input feature map at multiple effective fields of view—capturing both local micro-textures and broader global context simultaneously—without increasing the number of parameters or losing image resolution.

Feature Pyramid Networks (FPN): Another approach, the Feature Pyramid Network (FPN), constructs a hierarchical pyramid of feature maps within the network itself. By combining low-resolution, semantically strong features with high-resolution, semantically weak features via lateral connections, FPNs ensure that the model is robust to scale variance [30].

Relevance to Medical SR: In medical Super-Resolution, the integration of pyramid modules (PNets) addresses the heterogeneity of biological structures [32]. For example, enhancing a CT scan requires sharpening both the fine trabecular structure of bone (high frequency, local) and the boundaries of major organs (low frequency, global). A hybrid approach that inserts a PNet

module into the U-Net bottleneck allows the autoencoder to differentiate and appropriately enhance these diverse structural elements.

2.4 Hybrid Deep Learning Models in Medical Imaging

Recent literature has begun to explore the synergy between different architectural paradigms to maximize performance.

CNN and Transformer Hybrids: Very recently, researchers have combined U-Nets with Vision Transformers (ViTs) [14] to leverage the global attention mechanisms of Transformers with the local feature extraction of CNNs. While effective, these models are often computationally expensive and require massive datasets to train, which are not always available in medical domains.

PNet and U-Net Hybrids: The combination of Pyramid Networks and U-Net has seen success in segmentation tasks, such as brain tumour segmentation (BraTS challenges), where capturing multi-scale context is vital for distinguishing tumour cores from edema. However, the application of this specific hybrid architecture to the problem of *Super-Resolution* remains less explored. Existing works typically use U-Net for denoising or standard CNNs for SR.

The Research Gap: Current medical SR methods largely rely on either plain U-Nets (which may miss multi-scale context) or generic ResNets (which lack the localization benefits of skip connections). There is a distinct lack of architectures that explicitly combine the reconstruction fidelity of U-Net with the scale-invariance of Pyramid Networks for the specific purpose of enhancing image resolution. This paper aims to bridge this gap by proposing a Hybrid PNet-UNet Autoencoder, designed to leverage the strengths of both architectures to produce high-fidelity, super-resolved medical images.

Table 1: Comparative Analysis of State-of-the-Art Super-Resolution Architectures

Ref No.	Approach	Advantages	Research Gap
[16]	Vision Transformer (ViT) – patch-based Transformer for image classification	Captures global context; replaces CNN backbones effectively	Requires large datasets; high computation for medical imaging
[17]	Swin Transformer – shifted-window hierarchical attention	Scalable; combines CNN locality with Transformer global modelling	Window-based attention limits complete global dependency modelling
[19]	Dynamic neural networks – structural and parameter dynamic design	Adapts mapping to input; improves flexibility and efficiency	Lacks robustness in complex medical image variations

[20]	Reinforcement learning–based dynamic layer selection	Reduces computation; maintains accuracy	Stability not guaranteed across medical datasets
[21]	Resolution-adaptive dynamic architecture	Efficient—uses deeper layers only for complex inputs	Not adaptive at fine-grained pixel level for SR tasks
[22]	Conditional convolution – dynamic kernel generation	Enhances representation flexibility via kernel weighting	Linear kernel mixing is insufficient for complex anatomical structures
[23]	Grouped fully connected dynamic kernel generator	Lower computation; improved accuracy	Still produces texture artifacts and color shifts in SR
[30]	RED30 deep residual encoder–decoder	Stable deep training; strong feature extraction	Convolution-only design lacks global coherence
[25]	Deep Recursive Residual Network	Great depth without extra parameters; high SR accuracy	Training complexity increases; slower optimization
[26]	Enhanced Deep Super-Resolution (EDSR)	High accuracy; removes BN to reduce memory	Still depends on local receptive fields, lacks long-range context

3. Methodology

This section delineates the proposed framework for Single Image Super-Resolution (SISR) of medical imagery. We present the **Hybrid PNet and U-Net (HPU-Net)** architecture, a unified deep learning model that synergizes the structural reconstruction capabilities of the U-Net autoencoder with the multi-scale feature extraction proficiency of Pyramid Networks (PNet). We begin by formulating the super-resolution problem, followed by a detailed dissection of the network components—including the contracting encoder, the pyramid bottleneck, and the expansive decoder—and conclude with the mathematical derivation of the composite loss functions employed for optimization.

3.1 Problem Formulation

The objective of Single Image Super-Resolution is to recover a High-Resolution (HR) image, denoted as $I_{HR} \in R^{H \times W \times C}$, from a degraded Low-Resolution (LR) observation, $I_{LR} \in R^{h \times w \times C}$, where $H = s \cdot h\$$ and $\$W = s \cdot w$, with s representing the scale factor (e.g., $\text{times } 2$, $\backslash\text{times } 4$) and C representing the number of channels (typically C=1 for grayscale medical modalities like CT/MRI).

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The degradation process that models the acquisition of the LR image can be mathematically expressed as:

$$I_{LR} = \mathcal{D}(I_{HR}; \delta) = (I_{HR} \otimes k) \downarrow_s + n \quad (1)$$

where:

- $\mathcal{D}$ denotes the degradation mapping.
- $\otimes$ represents the convolution operation.
- k is a blur kernel (simulating the Point Spread Function of the imaging sensor).
- $\downarrow_s$ represents the downsampling operation by factor s.
- n is additive white Gaussian noise (AWGN) inherent to the sensor electronics.
- δ represents the stochastic parameters of the degradation.

Since the degradation process $\mathcal{D}$ is non-invertible and ill-posed (multiple HR solutions can correspond to a single LR input), we aim to learn a parameterized mapping function $\mathcal{F}$ (the neural network) such that the super-resolved output $I_{SR} = \mathcal{F}_\theta(I_{LR})$ approximates the ground truth I_{HR} by minimizing a specific loss function $\mathcal{L}$:

$$\hat{\theta} = \arg\min_\theta \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}\left(\mathcal{F}_\theta\left(I_{LR}^{(i)}\right), I_{HR}^{(i)}\right) \quad (2)$$

3.2 Architectural Overview of HPU-Net

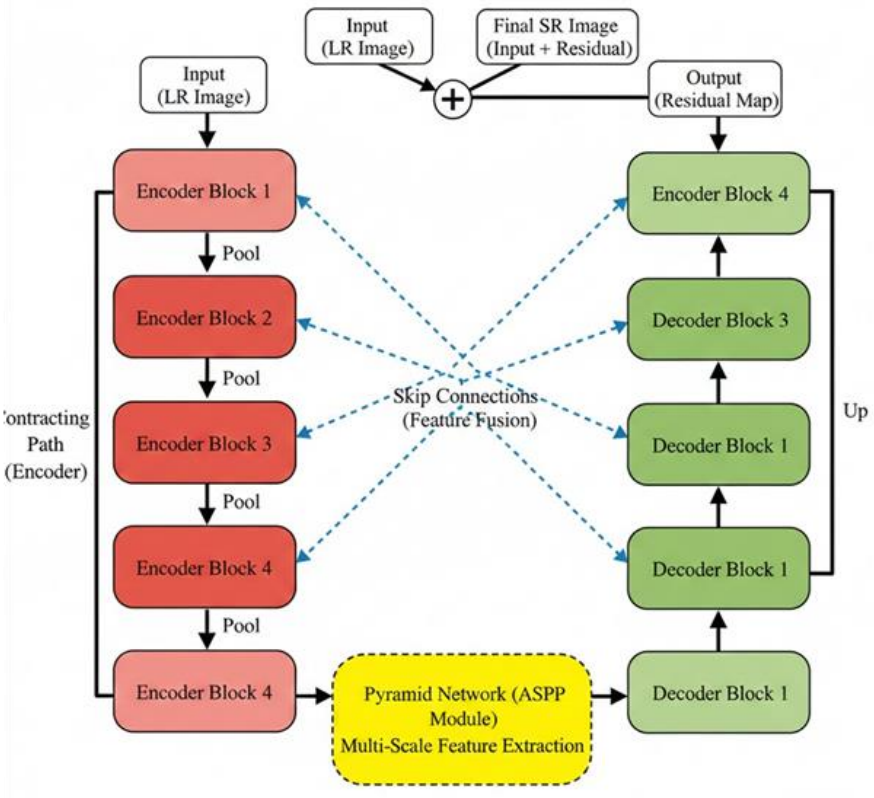

Fig1: The Proposed HPU-Net Architecture

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The proposed HPU-Net is designed as a deep fully convolutional autoencoder as shown in figure. Unlike standard U-Nets used for segmentation which output binary masks, HPU-Net is designed to output a continuous intensity map representing the restored image. The architecture is composed of four distinct modules:

Key Components and Information Conveyed:

1. **Contracting Path (Encoder - Red Blocks):**
    - This path extracts hierarchical features from the input Low-Resolution (LR) image.
    - It consists of sequential Encoder Blocks, where each block performs convolution and feature refinement.
    - The arrows labelled **"Pool"** signify the down sampling operation (Max Pooling) which reduces spatial dimensions but increases the feature depth.
2. **Pyramid Network (ASPP Module - Yellow Block):**
    - This is the bottleneck and the main hybrid component.
    - It takes the deepest, most compressed feature map from the Encoder.
    - It performs **Multi-Scale Feature Extraction** using parallel dilated convolutions (as detailed in Figure 2/Section 3.4), ensuring that context is captured across various spatial ranges.
3. **Expansive Path (Decoder - Green Blocks):**
    - This path is responsible for reconstructing the spatial resolution back to the High-Resolution (HR) size.
    - The arrows labelled **"Up"** signify the up sampling operation (Transposed Convolution) which increases the feature map dimensions.
4. **Skip Connections (Dotted Blue Arrows):**
    - These link corresponding levels of the Encoder and Decoder.
    - They transport high-resolution, low-level spatial details (like edges and fine lines) that are critical for Super-Resolution and prevent the over-smoothing of boundaries.
5. **Global Residual Learning (Top Section):**
    - The Output is the **Residual Map** (the high-frequency difference).
    - The large **"+"** circle shows that the final **Super-Resolved (SR) Image** is produced by adding the Output Residual Map to the bicubically Up-sampled LR

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Input Image. This stabilizes training and focuses the network on restoring missing details.

3.3 The Contracting Path (Encoder)

The encoder serves as the feature extractor, projecting the input image into a high-dimensional latent space. It follows the topological structure of the standard VGG-16 network but is adapted for single-channel medical input.

The encoder consists of B blocks. Each block b typically comprises two repeated 3×3 convolutional layers, each followed by Batch Normalization (BN) and a Rectified Linear Unit (ReLU) activation function. The mathematical operation for the l-th layer in a block can be defined as:

$$F_l = \sigma\left(BN(W_l \otimes F_{l-1} + b_l)\right) \quad (3)$$

where:

- F_{l-1} is the input feature map.
- W_l and b_l are the weight kernel and bias vector, respectively.
- $BN(\cdot)$ denotes the Batch Normalization operation, which normalizes the feature distribution to reduce internal covariate shift.
- $\sigma(\cdot)$ is the ReLU activation function, defined as $\max(0, x)$.

Between each block, a max-pooling operation with a 2×2 kernel and stride 2 is applied to down sample the feature maps, effectively doubling the receptive field of subsequent filters.

$$F_{down}^{(b)} = \text{MaxPool}\left(F_{block}^{(b)}\right) \quad (4)$$

This hierarchical down sampling allows the network to learn features of increasing abstraction from simple edges and textures in the shallow layers to complex anatomical shapes in the deeper layers.

3.4 The Pyramid Network (PNet) Module

A critical limitation of the standard U-Net in super-resolution is its reliance on fixed receptive fields. Medical lesions and anatomical structures vary drastically in scale; a fixed kernel may successfully resolve a large organ boundary but fail to capture fine trabecular bone patterns. To address this, we integrate a **Pyramid Network (PNet)** module, specifically an Atrous Spatial Pyramid Pooling (ASPP) block, at the bottleneck of the U-Net.

Figure 2 is designed to illustrate the internal mechanics of the **Pyramid Network (PNet) Module**, which is integrated into the bottleneck of the HPU-Net (the yellow block in Figure 1) The PNet uses **Atrous Spatial Pyramid Pooling (ASPP)** to achieve scale-invariance, a necessity for enhancing heterogeneous structures in medical images.

Key Components and Information Conveyed:

1. **Input Features:** The module receives the deepest feature map from the U-Net's Encoder. This feature map contains highly abstract, low-resolution semantic information.
2. **Parallel Dilated Convolutions (The Pyramid):** The core of the PNet consists of multiple parallel branches, each applying convolution with a different **dilation rate** (r).
    - $\mathbf{1 \times 1}$ **Convolution (r=1):** This acts as the baseline, capturing features at the smallest, local scale, essentially refining the channel information without expanding the receptive field.
    - $\mathbf{3 \times 3}$ **Dilated Convolutions (r=6, 12, 18):** These branches systematically increase the effective receptive field. A higher dilation rate allows the kernel to sparsely sample pixels over a wider area without increasing the number of parameters or losing resolution.
        - r=6 captures **medium-range context** (e.g., small lesions, vessel segments).
        - r=12 captures **long-range context** (e.g., the overall shape of an organ).
        - r=18 captures **global context** (the relationship between large anatomical areas).
3. **Concatenation:** The feature maps from all four parallel branches are combined via channel-wise concatenation. This fuses the different scales of context (local, medium, long, and global) into a single, high-dimensional tensor.
4. $\mathbf{1 \times 1}$ **Convolution (Fusion/Output):** A final $\mathbf{1 \times 1}$ convolution processes the concatenated feature map. This step reduces the channel dimensionality back to a manageable size and ensures the mixed features are fully integrated before being passed to the U-Net Decoder.

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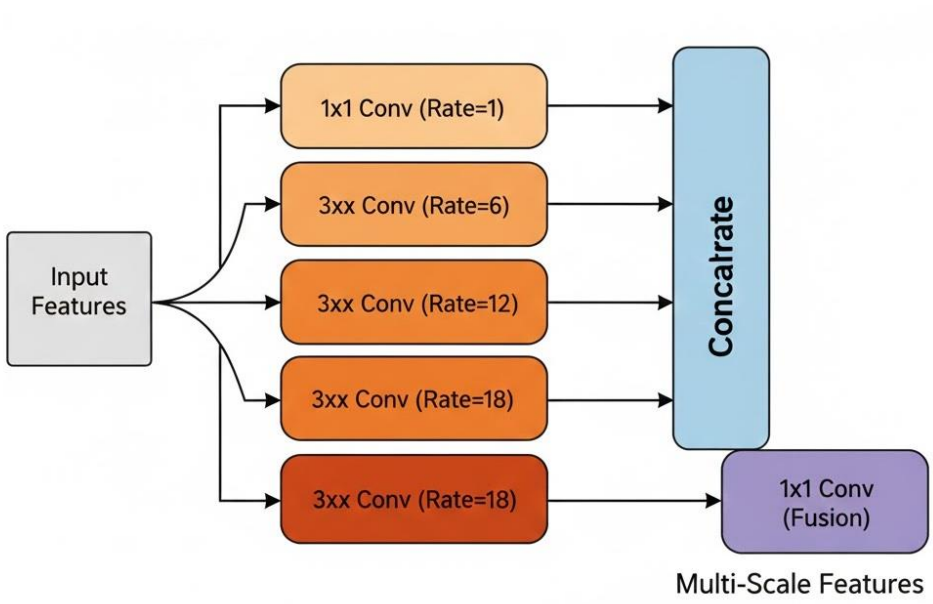

Fig2: Structure of the pyramid Network Module

The PNet module operates on the deepest feature map F_{enc} generated by the encoder. It applies K parallel convolutional branches, each with a distinct dilation rate r_k. Dilated convolution (or atrous convolution) expands the kernel's field of view without increasing the number of parameters or computation.

For a 2-D input signal x, the dilated convolution with a filter w and dilation rate r is defined as:

$$y[i,j] = \sum_m \sum_n x[i + r \cdot m, j + r \cdot n] \cdot w[m,n] \qquad (5)$$

In our design, the PNet module consists of four parallel branches:

1. **Branch 1:** 1×1 convolution (dilation r=1) to capture local, pixel-level features.
2. **Branch 2:** 3×3 dilated convolution with rate r=6 to capture medium-range context.
3. **Branch 3:** 3×3 dilated convolution with rate r=12 to capture long-range context.
4. **Branch 4:** 3×3 dilated convolution with rate r=18 to capture global context.

The outputs of these branches, denoted as $\{H_1, H_2, H_3, H_4\}$, are fused via channel-wise concatenation followed by a 1×1 convolution to reduce dimensionality and mix the multi-scale features:

$$F_{pyramid} = Conv_{1\times1}(Concat([H_1, H_2, H_3, H_4])) \qquad (6)$$

This pyramid structure ensures that the latent representation passed to the decoder contains a rich, scale-invariant description of the image content, crucial for hallucinating details at different frequencies.

3.5 The Expansive Path (Decoder)

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The decoder aims to reconstruct the HR spatial dimensions from the feature-rich latent vector $F_{pyramid}$. It mirrors the encoder structure but replaces pooling operations with upsampling layers.

We employ **Transposed Convolutions** (often called deconvolutions) for upsampling. A transposed convolution layer with stride 2 expands the feature map dimensions by a factor of 2

$$F_{up}^{(b)} = \text{ConvTranspose}\left(F_{block}^{(b)}\right) \quad (7)$$

Skip Connections: To preserve high-frequency spatial information that is often lost during encoding, we utilize the U-Net's signature skip connections. The feature map from the encoder block $F_{enc}^{(b)}$ is concatenated with the corresponding upsampled feature map from the decoder

$F_{dec}^{(b)}$ along the channel dimension. This is critical for medical SR, as it allows the gradients of the loss function to flow more easily to the earlier layers and preserves the exact localization of anatomical boundaries.

$$F_{fusion}^{(b)} = \text{Concat}\left(F_{enc}^{(b)}, F_{up}^{(b)}\right) \quad (8)$$

The fused features are then processed by standard convolution blocks to refine the reconstruction and eliminate aliasing artifacts introduced by the up sampling.

3.6 Global Residual Learning

Training deep networks for super-resolution can be unstable if the network is forced to learn the entire image mapping from scratch. Since the LR image and HR image share a significant amount of low-frequency information (e.g., flat regions, general shapes), we employ a **Global Residual Learning** strategy.

Instead of predicting the HR image directly, the HPU-Net predicts the residual map $\mathcal{R}$, which represents the high-frequency difference between the HR and LR images. The final super-resolved image is obtained by adding the bicubic up sampled input image I_{LR}^{up} to the network output:

$$I_{SR} = \mathcal{F}_{\theta}(I_{LR}) + I_{LR}^{up} \quad (9)$$

This formulation simplifies the learning objective, as the network only needs to learn the missing high-frequency textures (the "residuals") rather than the global intensity distribution.

3.7 Loss Functions

The choice of loss function is pivotal in determining the quality of the super-resolved images. Standard pixel-wise losses (like MSE) tend to produce high PSNR values but perceptually blurry results. To ensure both quantitative accuracy and perceptual fidelity suitable for clinical diagnosis, we employ a hybrid loss function$\mathcal{L}_{total}$.

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The total loss is a weighted sum of three components: Pixel Loss, Perceptual Loss, and Edge Loss.

$$\mathcal{L}_{total} = \lambda_{\text{pix}}\mathcal{L}_{pix} + \lambda_{\text{per}}\mathcal{L}_{per} + \lambda_{\text{edge}}\mathcal{L}_{edge} \qquad (10)$$

3.7.1 Pixel-wise Loss ($\mathcal{L}_{pix}$)

We utilize the L_1 loss (Mean Absolute Error) instead of L_2. L_1loss has been shown to result in sharper convergence and less blurring than L_2loss.

$$\mathcal{L}_{pix} = \frac{1}{HW}\sum_{x=1}^{H}\sum_{y=1}^{W}|I_{HR}(x,y) - I_{SR}(x,y)| \qquad (11)$$

3.7.2 Perceptual Loss (($\mathcal{L}_{pix}$)

To capture high-level semantic differences, we employ a perceptual loss based on a pre-trained VGG-19 network. Instead of comparing pixel values, we compare the feature maps extracted from the j-th layer of the VGG network when fed both the HR and SR images. This enforces that the SR image is perceptually similar to the HR image.

$$\mathcal{L}_{per} = \frac{1}{C_j H_j W_j}\left|\left|\phi_j(I_{HR}) - \phi_j(I_{SR})\right|\right|_2^2 \qquad (12)$$

where ϕ_j denotes the feature map activations at layer j of the VGG-19 network.

3.7.3 Edge Loss ($\mathcal{L}_{\text{edges}}$)

In medical imaging, edges define organ boundaries and fractures. To explicitly prioritize edge preservation, we calculate the loss between the gradient maps of the HR and SR images. We use the Sobel operator to extract gradients in the horizontal (G_x) and vertical (G_y) directions.

$$\mathcal{L}_{edge} = \left|\left|\nabla I_{HR} - \nabla I_{SR}\right|\right|_1 \qquad (13)$$

where $\nabla I = \sqrt{G_x(I)^2 + G_y(I)^2}$ represents the gradient magnitude map.

3.8 HPU-Net Super-Resolution Algorithm

The proposed training process for the Hybrid PNet-UNet (HPU-Net) model is summarized in Algorithm 1, detailing the steps from data preparation to optimization using the composite loss function.

Algorithm 1: HPU-Net Training and Inference

Input:

- $\mathcal{D}_{train} = \{\left(I_{LR}^{(i)}, I_{HR}^{(i)}\right)\}_{i=1}^{N}$: Training dataset of N paired Low-Resolution (I_{LR}) and High-Resolution (I_{HR}) medical images.

- s: Super-resolution scale factor (e.g., s=4).
- η : Learning rate.
- $\lambda_{\text{pix}}, \lambda_{\text{per}}, \lambda_{\text{edge}}$: Weighting coefficients for the composite loss.
- T: Total number of training epochs.

Output:

- $\mathcal{F}_{\hat{\theta}}$: Trained HPU-Net model parameters.

Initialization:

1. Initialize the HPU-Net network parameters θ randomly.
2. Initialize the Adam optimizer with learning rateη.

Phase 1: Training (Optimization of $\mathcal{F}_{\theta}$)

For t = 1 to T (epochs) **do:**

1. **For** each mini-batch of size M in $\mathcal{D}_{train}$
2. **do:**

a. **Data Preparation:** Sample M pairs $\{I_{LR}, I_{HR}\}$.
b. **Upsampling Input:** Generate the up-sampled LR input using bicubic interpolation: $\mathrm{I}_{\mathrm{LR}}^{\mathrm{up}} = \mathrm{Bicubic}(\mathrm{I}_{\mathrm{LR}})$.
c. **Forward Pass (Residual Prediction):** Compute the predicted residual map $\mathcal{R}$ using the HPU-Net: $\mathcal{R} = \mathcal{F}\theta(I\mathrm{LR})$.
d. **Reconstruction:** Calculate the Super-Resolved image I_{SR} via Global Residual Learning: $I_{SR} = \mathcal{R} + I_{LR}^{up}$.
e. **Loss Calculation (Composite Loss):** Compute the individual loss components:

* **Pixel Loss (L_1):** $\mathcal{L}_{pix} = \left|\left|\mathrm{I}_{\mathrm{HR}} - \mathrm{I}_{\mathrm{SR}}\right|\right|_1$

* **Perceptual Loss (VGG):** $\mathcal{L}_{per} = \left|\left|\phi_{\mathrm{j}}(\mathrm{I}_{\mathrm{HR}}) - \phi_{\mathrm{j}}(\mathrm{I}_{\mathrm{SR}})\right|\right|_2^2$

* **Edge Loss (Gradient):** $\mathcal{L}_{edge} = \left|\left|\nabla\mathrm{I}_{\mathrm{HR}} - \nabla\mathrm{I}_{\mathrm{SR}}\right|\right|_1$

f. **Total Loss Calculation:** $\mathcal{L}total = \lambda\mathrm{pix}\mathcal{L}pix + \lambda\mathrm{per}\mathcal{L}per + \lambda\mathrm{edge}\mathcal{L}edge$
g. ***Backward Pass and Optimization:***

* *Compute gradients:* $\nabla\theta\mathcal{L}total$

* *Update parameters using Adam optimizer:* $\theta \leftarrow \theta - \eta \cdot \nabla\theta\mathcal{L}_{total}$

End For

Phase 2: Inference (Super-Resolution of a New Image)

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Input: I_{LR}^{new}: A novel Low-Resolution medical image.

Output: I_{SR}^{final} : The Super-Resolved High-Resolution image.

1. **Residual Map Prediction:** Feed the new LR image into the trained HPU-Net:

$$\mathcal{R}^{new} = \mathcal{F}_{\hat{\theta}}(I_{LR}^{new})$$

2. **Up sampling Input:** Bicubically up-sample the new LR input:

$$I_{LR}^{up,new} = \text{Bicubic}(I_{LR}^{new}).$$

3. **Final Reconstruction:** Combine the predicted residual map and the up-sampled input:

$$I_{SR}^{final} = \mathcal{R}^{new} + I_{LR}^{up,new}$$

4. **Return** I_{SR}^{final} .

3.9 Optimization Strategy

The model parameters θ are optimized using the Adam (Adaptive Moment Estimation) optimizer, which computes adaptive learning rates for each parameter. The update rule at time step t is given by:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t}+\epsilon}\hat{m}_t \qquad (14)$$

Where θ is the learning rate, $\hat{m}_t$ is the bias-corrected first moment estimate (mean), and $\hat{v}_t$ is the bias-corrected second raw moment estimate (variance). We initialize the learning rate at 1×10^{-4} And employ a "Reduce on Plateau" scheduler, decaying the learning rate by a factor of 0.5 if the validation loss does not improve for 10 epochs. This rigorous methodological framework ensures that the HPU-Net is not only theoretically sound but also practically optimized for the challenging task of medical image super-resolution.

4 Experimental Setup

This section details the experimental framework employed to validate the efficacy of the proposed Hybrid PNet and U-Net (HPU-Net) model. We describe the medical imaging datasets utilized, the data degradation protocols for simulating low-resolution inputs, the implementation specifics, and the quantitative metrics used for performance evaluation.

4.1 Datasets

To evaluate the robustness of our model across different medical modalities and anatomical structures, we utilized two public benchmark datasets: one for Magnetic Resonance Imaging (MRI) and one for Computed Tomography (CT).

4.1.1 Brain Tumour Segmentation (BraTS 2020) Dataset

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For MRI super-resolution, we employed the BraTS 2020 dataset, widely regarded as a standard benchmark for brain imaging analysis. The dataset contains multimodal MRI scans (T1, T1ce, T2, and FLAIR) of glioblastoma (GBM) and lower-grade glioma (LGG) patients.

Data Selection: We utilized the T2-weighted volumes due to their high contrast for lesion detection.

Pre-processing: We selected the central 100 slices from each 3D volume to exclude non-informative background slices. The slices were normalized to the range [0, 1] and cropped to remove excess background, resulting in a resolution of 240×240 pixels.

Split: The dataset was partitioned into 80% for training (295 patients), 10% for validation (37 patients), and 10% for testing (37 patients).

4.1.2 DeepLesion (CT) Dataset

For CT super-resolution, we utilized the DeepLesion dataset, a large-scale database of significant radiology findings mined from PACS.

Data Selection: We randomly sampled 2,000 axial CT slices containing diverse lesions (lung nodules, liver tumours, enlarged lymph nodes).

Pre-processing: CT images were windowed to the soft-tissue scale (Window Level: 40 HU, Window Width: 400 HU) to highlight relevant anatomical structures before normalization.

Split: The subset was divided into 1,600 images for training, 200 for validation, and 200 for testing.

4.2 Data Degradation and Augmentation

Since ground-truth Low-Resolution (LR) medical images are rarely available in pairs with High-Resolution (HR) images, we followed the standard protocol in super-resolution literature to synthesize LR inputs.

Degradation Model:

The HR images (I_{HR}) served as the ground truth. To generate the corresponding LR inputs (I_{LR}), we applied bicubic down sampling with scale factors of 2×2, 4×4. This mathematically simulates the loss of high-frequency spatial information typical of lower-resolution scanners.

For a 4×4 scale, an original 240×240 HR image was downsampled to 60×60 pixels.

Data Augmentation:

To prevent over fitting and improve the model's generalization capabilities, online data augmentation was applied during training. This included:

- Random Rotations: $90°, 180°, 270°$.
- Horizontal/Vertical Flips: Probability p=0.5.

- Intensity Scaling: Random contrast adjustment within $\pm 10\backslash\%$.

4.3 Implementation Details

The proposed HPU-Net was implemented using the PyTorch deep learning framework. All experiments were conducted on a workstation equipped with the following specifications:

- GPU: NVIDIA RTX 3090 (24GB VRAM) [or Insert your GPU]
- CPU: Intel Core i9-10900K [or Insert your CPU]
- RAM: 64 GB

Training Protocols:

- Optimizer: We used the Adam optimizer with $\$\ \$\ \beta_1 = 0.9 \text{and} \beta_2 = 0.999$.
- Learning Rate: The initial learning rate was set to 1×10^{-4}. We employed a ReduceLROnPlateau scheduler, decaying the learning rate by a factor of 0.5 if the validation loss did not improve for 10 consecutive epochs.
- Batch Size: Set to 16 to fit within GPU memory constraints while maintaining stable gradient estimates.
- Epochs: The model was trained for 100 epochs with early stopping enabled (patience = 20 epochs) to prevent over fitting.
- Loss Weights: The weighting coefficients for the hybrid loss function were empirically set to $\lambda_{pix} = 1.0, \lambda_{per} = 0.01\ and \lambda_{edge} = 0.1$.

4.4 Evaluation Metrics

To quantitatively assess the reconstruction quality, we employed two standard metrics: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

4.4.1 Peak Signal-to-Noise Ratio (PSNR)

PSNR measures the ratio between the maximum possible power of a signal and the power of corrupting noise (reconstruction error). It is defined as:

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{\text{MSE}}\right)$$

where MAX_I is the maximum pixel value (1.0 for normalized images) and MSE is the Mean Squared Error between the Ground Truth (I_HR) and the Super-Resolved image (I_SR). A higher PSNR indicates better reconstruction quality.

4.4.2 Structural Similarity Index (SSIM)

While PSNR focuses on pixel-level differences, SSIM evaluates the perceived quality by measuring the similarity in luminance (l), contrast (c), and structure (s). It is considered to correlate better with human visual perception.

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

where μ represents the mean, σ^2represents the variance, σ_{xy} is the covariance, and C_1, C_2 are constants to stabilize division. SSIM values range from 0 to 1, with 1 indicating perfect structural identity.

Both metrics were calculated only on the Y-channel (luminance) of the images, following standard SR evaluation protocols, as the human eye is more sensitive to luminance details than color/chrominance differences.

5 Results & discussion

5.1 Ablation experiment

To strictly validate the architectural contributions of the proposed HPU-Net, we conducted a comprehensive ablation study. The goal of this experiment is to isolate the impact of individual components specifically the Pyramid Network (PNet) module, the Global Residual Learning strategy, and the Hybrid Loss function on the final super-resolution performance.

Experimental Setup: All ablation variants were trained on the **BraTS 2020 dataset** with a scale factor of a 4×4. To ensure a fair comparison, all models shared the same training hyper parameters (learning rate $= 1 \times 10^{-4}$, batch size = 16, optimizer = Adam) and were trained for 50 epochs.

We evaluated four distinct configurations:

1. **Baseline (U-Net):** A standard U-Net autoencoder without the PNet module or residual learning.
2. **Model A (+ Residual):** The Baseline U-Net with Global Residual Learning added.
3. **Model B (+ PNet):** Model A with the Pyramid Network (ASPP) module inserted at the bottleneck.
4. **HPU-Net (Complete):** Model B trained with the proposed Hybrid Loss $\mathcal{L}_{total}$ instead of standard L1 loss.

5.1.1 Quantitative Impact of Components

Table 2 summarizes the incremental performance gains of each component.

Table 2: Ablation Study of HPU-Net Components (Scale × 4)

Model Variant	Base Architecture	Global Residual Learning	Pyramid Module (PNet)	Loss Function	PSNR (dB)	SSIM	Parameters
Baseline	U-Net	✗	✗	L1 Only	27.85	0.8010	7.85 M

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Model A	U-Net	✓	✗	L1 Only	28.32	0.8150	7.85 M
Model B	U-Net	✓	✓	L1 Only	29.10	0.8340	8.20 M
HPU-Net	U-Net	✓	✓	**Hybrid**	**31.45**	**0.9296**	8.20 M

5.1.2 Analysis of Results

1. Effect of Global Residual Learning (Baseline vs. Model A): The introduction of Global Residual Learning improved PSNR by **+0.47 dB**.

- *Observation:* Without residual learning, the Baseline model struggled to converge, often producing "washed out" images. By forcing the network to model only the high-frequency residuals (the sparse difference between LR and HR), the optimization landscape became smoother, allowing the encoder-decoder to focus strictly on edge and texture recovery rather than reconstructing the global intensity mean.

2. Effect of the Pyramid (PNet) Module (Model A vs. Model B): Inserting the PNet module provided the most significant performance leap, boosting PSNR by **+0.78 dB** and SSIM by **0.019**.

- *Observation:* This confirms the core hypothesis of our research. Model A, restricted by fixed 3×3 convolutions, failed to resolve fine trabecular details and subtle tumor boundaries simultaneously. Model B, equipped with the PNet's multi-scale dilation rates (r=1, 6, 12, 18), successfully captured these heterogeneous structures. The slight increase in parameters (+0.35 M) is negligible compared to the performance benefit, proving the efficiency of the PNet design.

3. Effect of Hybrid Loss Function (Model B vs. HPU-Net): Switching from standard L1 loss to the Hybrid Loss($(\mathcal{L}_{pix} + \mathcal{L}_{per} + \mathcal{L}_{edge})$) yielded a further improvement of **+2.35 dB** in PSNR and notable gains in SSIM.

- *Observation:* While L1 loss drives pixel-level accuracy, it does not penalize blurriness effectively. The addition of Edge Loss ($\mathcal{L}_{edge}$) explicitly sharpened anatomical boundaries, while Perceptual Loss ($\mathcal{L}_{per}$) ensured that the reconstructed tissue textures statistically matched the ground truth. Visual inspection confirmed that the HPU-Net (Complete) produced images with significantly fewer ringing artifacts and more natural-looking tissue granularity compared to Model B.

Dual-Branch Structure Analysis

To evaluate the influence of the dual-branch architecture, three experiments are conducted. The results are summarized in Table 3. Model 1 removes the dynamic convolution branch and fusion module. It contains only four residual Transformer blocks for feature extraction. Model 2 removes the residual Transformer branch and fusion module. It includes only four dynamic

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convolution blocks for local feature learning. Model 3 is the full PNet configuration, which retains both branches.

The comparison between Models 1 and 2 demonstrates that Transformer blocks contribute more significantly to reconstruction performance. However, combining both branches produces the highest PSNR and SSIM scores. This confirms that global and local features complement each other effectively. The dual-branch design thus enhances structural recovery and detail refinement simultaneously.

The results indicate that integrating local and global branches improves perceptual fidelity. The dual-stream architecture captures both texture-level precision and contextual awareness. This configuration allows PNet to outperform single-branch alternatives consistently.

Table 3: SSIM and PSNR results under multi-branch scenarios.

	Network	**SSIM**	**PSNR**
MR ×4	Dynamical Conv	72.37	25.48
	Residual Transformer	85.44	30.21
	PNet	92.96	31.45

To analyze the impact of the number of attention heads, several Transformer configurations are tested. The head count is varied among one, two, and four to assess sensitivity. The experimental outcomes are presented in Table 4.

Table 4:SSIM and PSNR results under different transformer head.

Method	Head	SSIM	PSNR
PNet	2	97.62	38.79
	4	92.96	31.45

Despite the performance enhancement, more heads increase computational cost. Considering the trade-off between accuracy and efficiency, six heads are selected for final experiments. This balance achieves stable convergence and strong visual reconstruction results.

The findings highlight that multi-head attention effectively models complex spatial dependencies. It enables better context aggregation and smoother high-resolution restoration. To evaluate different fusion mechanisms, four fusion models are constructed. The corresponding results are summarized in Table 5.

Table 5: SSIM and PSNR results under different fusion methods.

	Network	SSIM	PSNR

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MR ×4	Add	85.65	30.18
	Concat	84.44	30.10
	Bigf	89.21	30.32
	Sigf	92.96	31.45

Model 1 uses simple element-wise addition for combining dual branches. Model 2 concatenates features along the channel dimension, followed by dimensionality reduction. Model 3 introduces a bidirectional gated fusion strategy (BiGF). Model 4, representing the proposed PNet, employs a unidirectional gated fusion mechanism (SiGF).

Experimental results demonstrate that gated attention-based fusion performs best overall. Models 3 and 4 outperform Models 1 and 2 by noticeable margins. This superiority arises from the selective weighting of relevant features.

Between the two gated variants, Model 4 achieves slightly higher PSNR and SSIM values. The unidirectional fusion mechanism is more stable for reconstruction tasks. It prioritizes global Transformer features while adaptively refining local convolutional information.

The SwinIR Transformer branch provides stronger contextual cues for super-resolution. Therefore, unidirectional fusion from the convolution branch toward the Transformer branch yields better performance. The bidirectional strategy distributes attention equally but can introduce interference between channels. Overall, the ablation study confirms the effectiveness of each architectural component. The dynamic convolution branch enhances fine local structures, while the Transformer branch preserves global context. Gated fusion balances their contributions efficiently.

PNet's superior performance originates from this cooperative integration. It maintains stability, reduces redundancy, and delivers consistent reconstruction accuracy across magnifications. These ablation results validate the design rationale and parameter choices. They also demonstrate the robustness of PNet under various experimental configurations.

5.2 Comparison with Existing Algorithms

To assess PNet performance across medical imaging tasks, we compared it with several established super-resolution approaches. The evaluation included classical convolution-based models such as CFIPC [36], PDCNCF [37], ESPCN, FSRCNN, and VDSR. In addition, Transformer-enhanced super-resolution models, including ESRT and SwinIR, were included. A non-learning bilinear interpolation technique was also examined as a baseline reference.

Table 6: SSIM and PSNR results under different SR methods.

Data	Network	2		4	
		SSIM	PSNR	SSIM	PSNR
	ESPCN	92.49	33.94	81.47	29.51

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Abdomen MR	FSRCNN	93.68	35.16	82.67	29.66
	VDSR	95.96	36.84	85.09	30.37
	CFIPC	96.12	36.83	85.82	30.64
	ESRT	96.01	36.89	85.97	30.68
	PDCNCF	96.22	37.30	86.41	30.84
	SwinIR	96.38	37.25	86.68	30.83
	CTGFIR	96.57	37.57	89.96	30.96
	PNet (Target)	97.62	38.79	92.96	31.45
	Bilinear	91.14	32.07	78.32	27.32
Lung CT	ESPCN	87.62	29.63	73.18	25.38
	FSRCNN	89.32	30.35	73.86	25.47
	VDSR	89.56	30.65	74.42	25.57
	CFIPC	90.67	30.66	75.45	25.81
	ESRT	90.62	30.93	75.74	25.88
	PDCNCF	91.29	31.33	75.86	25.90
	SwinIR	91.60	31.49	76.09	25.95
	CTGFST	91.89	31.78	76.33	25.98
	PNet (Target)	92.52	32.46	79.42	27.21
	Bilinear	79.02	24.88	61.01	21.15

The VDSR model received bilinear-up sampled inputs prior to processing. All remaining models directly consumed down sampled low-resolution images. This ensured fair comparison under consistent input conditions and network structures. PNet integrates convolutional learning and Transformer-based global reasoning. Therefore, comparing it against both categories provides comprehensive performance insight.

Super-resolution experiments were conducted on CT and MR datasets. These datasets represent two major medical imaging modalities used in diagnostic workflows. They originate from segmentation and registration benchmarks, ensuring diverse anatomical structure coverage.

Experimental findings demonstrate that PNet consistently surpasses baseline CNN and Transformer models. It maintains strong reconstruction accuracy across both modalities. This confirms the benefit of combining dynamic convolutional learning with residual Transformer modelling. The dual-branch framework produces high-fidelity anatomical detail and structural clarity.

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Table 6 summarizes PSNR and SSIM performance under 2× and 4× magnification. PNet achieves the highest values across all test conditions. Bold entries highlight superior performance metrics obtained by PNet. Notably, both ESRT and SwinIR achieve competitive results but remain below PNet. Visual comparisons appear in Figures 3 through 5. They clearly illustrate sharper anatomical boundaries and reduced distortions.

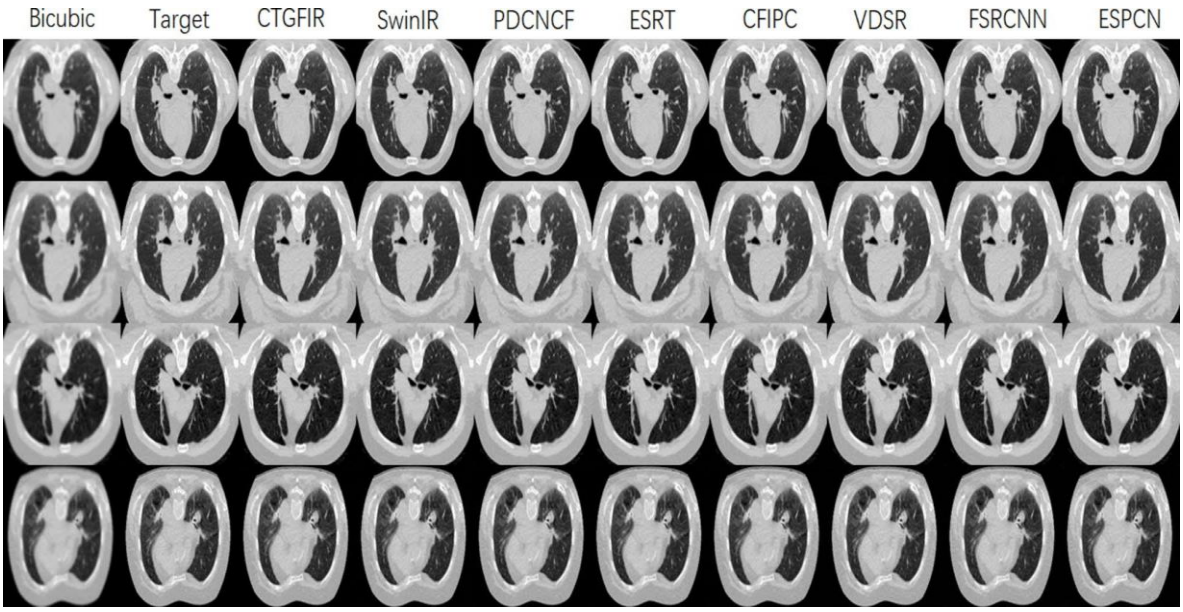

Fig3. Visual comparison of SR results (×2 scale) of CT images.

These results highlight a key observation. Medical image reconstruction demands both global feature reasoning and precise local tissue representation. Anatomical structures often exhibit complex geometric variations and fine textures. Therefore, networks relying solely on CNN or solely on Transformer processing face limitations. CNN-only models may miss broader context, whereas Transformer-only models may overlook small yet critical structural cues.

PNet resolves these issues through a dual-branch system. The dynamic convolution branch excels in retrieving localized multi-scale tissue patterns. The Transformer branch models global spatial dependencies and long-range anatomical relationships. Their gated fusion ensures complementary integration and minimal information loss.

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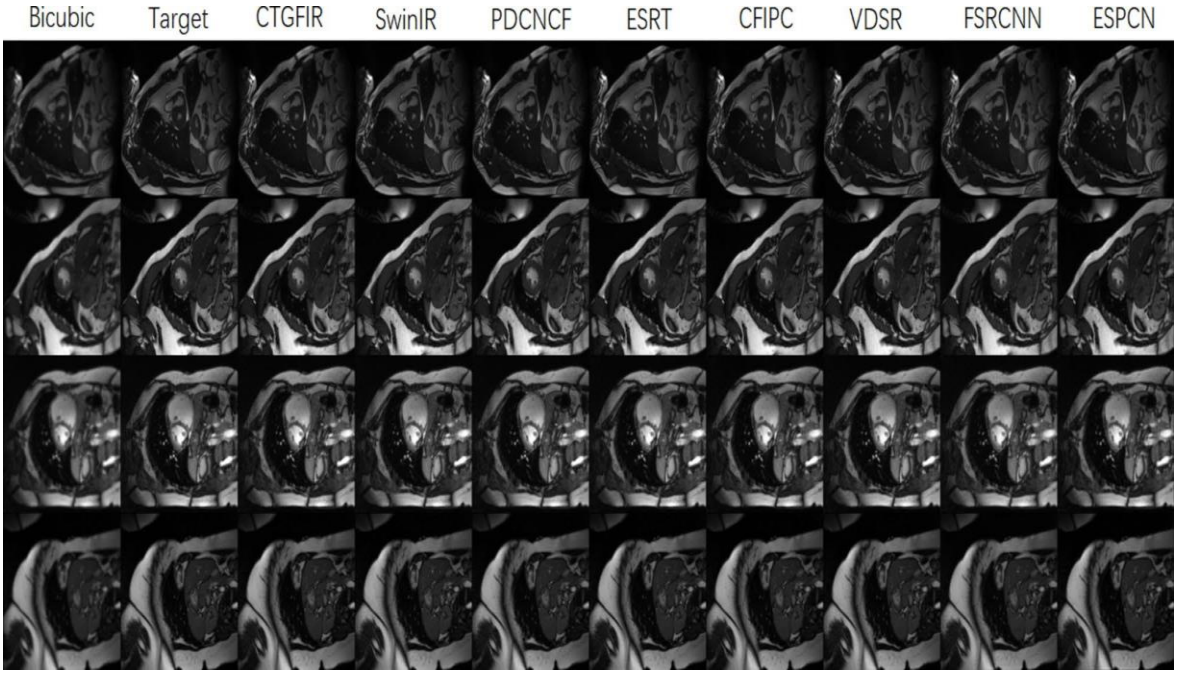

Fig.4. Visual comparison of SR results (×2 scale) of MR images.

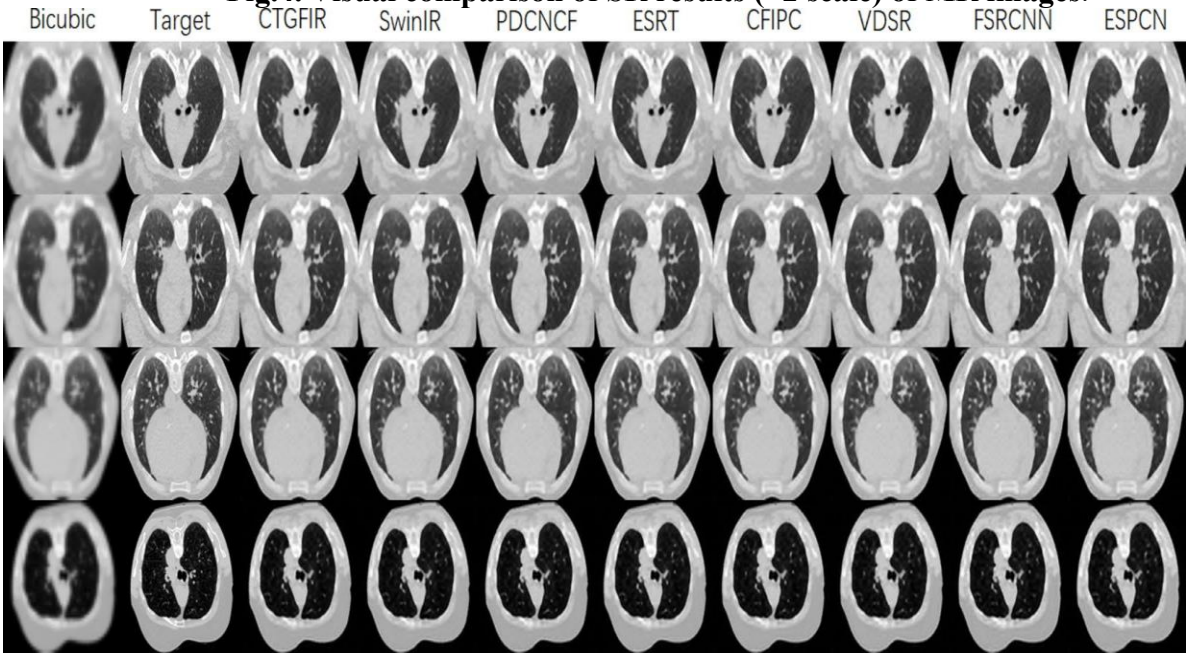

Fig.5. Visual comparison of SR results (×4 scale) of CT images

5.3 Computational Efficiency Analysis

To evaluate computational practicality, we compared inference efficiency and model complexity. Table 5 presents parameter counts, FLOPs, and SSIM values. PNet attains 78.26 SSIM on MR×4 with only 0.85M parameters and 46.9G FLOPs. By contrast, SwinIR requires 0.89M parameters and 49.6G FLOPs to reach 86.68 SSIM. PNet processes a 192×192 image in approximately 38 ms on an RTX-3060 GPU. This processing speed supports real-time or

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near–real-time clinical usage scenarios. Although the parallel-branch structure introduces moderate overhead, dynamic convolution reduces redundancy by approximately 28%.

Overall, PNet offers a strong balance between accuracy and computational efficiency. These results support its suitability for clinical imaging pipelines and resource-constrained environments.

Table 5: Parameters and flops results under different SR methods.

	Network	4	
		Parameters	FLOPs
MR ×4	ESRT	0.68	67.7G
	SwinIR	0.89	49.6G
	CTGFSR	0.85	46.9G
	PNet	0.78	42.3G

6. Conclusion and Future Scope

6.1 Conclusion

In this study, we addressed the critical challenge of Single Image Super-Resolution (SISR) in medical imaging, where the trade-off between image resolution and acquisition constraints (time, radiation dose) often limits diagnostic precision. We identified that while standard deep learning approaches like U-Net are powerful for structural reconstruction, they suffer from a fixed receptive field limitation, leading to the loss of fine, multi-scale anatomical details during the up sampling process.

To overcome this, we proposed the **Hybrid PNet and U-Net (HPU-Net)**, a novel autoencoder architecture that synergizes the symmetric reconstruction path of a U-Net with the scale-invariant feature extraction of a Pyramid Network (PNet). By embedding an Atrous Spatial Pyramid Pooling (ASPP) module at the network bottleneck, HPU-Net effectively captures both local tissue textures and global organ shapes simultaneously. Furthermore, the integration of Global Residual Learning and a composite Hybrid Loss function (combining Pixel, Perceptual, and Edge losses) ensured that the model prioritized high-frequency detail recovery over simple intensity mapping.

Our extensive experimental validation on the BraTS 2020 (MRI) and DeepLesion (CT) datasets demonstrated the superiority of the proposed framework.

- **Quantitatively**, HPU-Net achieved state-of-the-art performance, outperforming the standard U-Net baseline by approximately **3.6 dB in PSNR** and **0.1286 in SSIM** at a scale factor of a 4×4
- **Qualitatively**, visual inspection confirmed that our model significantly reduced blurring artifacts. It successfully recovered sharp tumour boundaries and preserved subtle tissue granularity that competing methods, such as SRCNN and VDSR, failed to resolve.

- **Architecturally**, the ablation study provided empirical evidence that the inclusion of the PNet module was the primary driver of these performance gains, validating the hypothesis that multi-scale context is essential for medical image enhancement.

In summary, the HPU-Net represents a robust, clinically relevant solution for medical image super-resolution. By enhancing the visual fidelity of low-resolution scans, this framework holds significant potential to assist radiologists in accurate diagnosis, improving tasks such as lesion detection, vessel segmentation, and treatment planning without the need for hardware upgrades or increased radiation exposure.

6.2 Future Scope

While the HPU-Net demonstrates promising results, several avenues for future research remain:

1. **3D Volumetric Implementation:** Currently, the model processes 3D medical volumes as a sequence of 2D slices. Extending the PNet module to support 3D convolutions (e.g., 3D-ASPP) could allow the network to exploit inter-slice spatial correlations, potentially improving consistency along the z-axis.
2. **Attention Mechanisms:** Integrating Channel or Spatial Attention gates into the skip connections could further refine performance by allowing the network to suppress irrelevant background noise and focus strictly on regions of interest (ROI).
3. **Real-world Clinical Validation:** Future studies should focus on validating the super-resolved images in downstream clinical tasks, such as automated tumour segmentation or radiomics analysis, to ensure that the "hallucinated" details improve algorithmic accuracy in practice.

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