AN AUTOMATED NEURAL ARCHITECTURE SEARCH FRAMEWORK FOR UNSUPERVISED PET IMAGE DENOISING

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Abstract

Positron Emission Tomography (PET) imaging plays a crucial role in oncology, neurology, and cardiology by enabling functional visualization of metabolic processes. However, PET images are inherently affected by low photon counts, Poisson noise, and reconstruction artifacts, which degrade image quality and compromise diagnostic reliability. Conventional denoising methods often rely on supervised learning frameworks that require paired clean and noisy datasets, which are difficult and expensive to obtain in real clinical environments. To address these limitations, this study proposes a Neural Architecture Search (NAS) framework for unsupervised PET image denoising that automatically discovers optimal neural network architectures without requiring clean ground-truth images during training.The proposed system integrates a self-supervised blind-spot learning strategy inspired by Noise2Void principles, enabling the model to learn noise distributions directly from corrupted PET data. Synthetic PET phantoms are generated to simulate realistic anatomical uptake patterns, and Poisson–Gaussian noise is applied to mimic photon-limited acquisition conditions. The NAS framework explores a structured search space comprising convolutional depth, channel width, kernel size, normalization layers, and residual skip connections. Each candidate architecture is trained using a masked self-supervised loss that predicts corrupted pixels from their surrounding context, thereby avoiding trivial identity mappings.A low-budget search strategy is employed to efficiently evaluate multiple candidate architectures based on validation self-supervised loss. The best-performing architecture is then retrained for extended epochs to achieve enhanced denoising performance. Experimental results on synthetic datasets demonstrate significant improvements in quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) compared to noisy inputs, validating the effectiveness of the automatically discovered architecture. Visual assessments further confirm that the proposed method preserves structural details while reducing stochastic noise artifacts.The key contributions of this work include: (1) a fully unsupervised PET denoising pipeline leveraging blind-spot learning, (2) an automated NAS-driven model optimization framework tailored for medical imaging, and (3) a reproducible synthetic PET simulation environment for benchmarking. The proposed approach reduces reliance on manually designed architectures and clean reference data, making it suitable for real-world low-dose PET imaging scenarios.