Revealing New Possibilities for Breast MRI Enhancement: Mamba-Driven Cross-Attention GAN with VMKANet

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Introduction

Breast cancer remains a critical global health threat, accounting for 32% of new cancer diagnoses in women (WHO). Dynamic Contrast-Enhanced MRI (DCE-MRI) is pivotal for tumor characterization but faces limitations due to gadolinium-based contrast agents (GBCAs), which pose risks like renal impairment and high costs. Non-contrast MRI alternatives underperform, creating a demand for synthetic DCE-MRI generation. Deep learning, particularly Generative Adversarial Networks (GANs), offers promising solutions. However, existing CNN-based models lack global context, while Transformers suffer from quadratic complexity. This study introduces a novel **Mamba-driven cGAN framework (VMKANet + CAViT)** to synthesize high-quality DCE-MRI from single-modality inputs. Our approach combines:

1. **Mamba's linear-time state-space modeling** for volumetric data efficiency.
2. **Kolmogorov-Arnold Networks (KAN)** for nonlinear feature fitting.
3. **Cross-Attention Vision Transformer (CAViT) discriminator** for distribution alignment.

This innovation aims to enhance accessibility, reduce costs, and eliminate GBCA risks while preserving diagnostic accuracy.

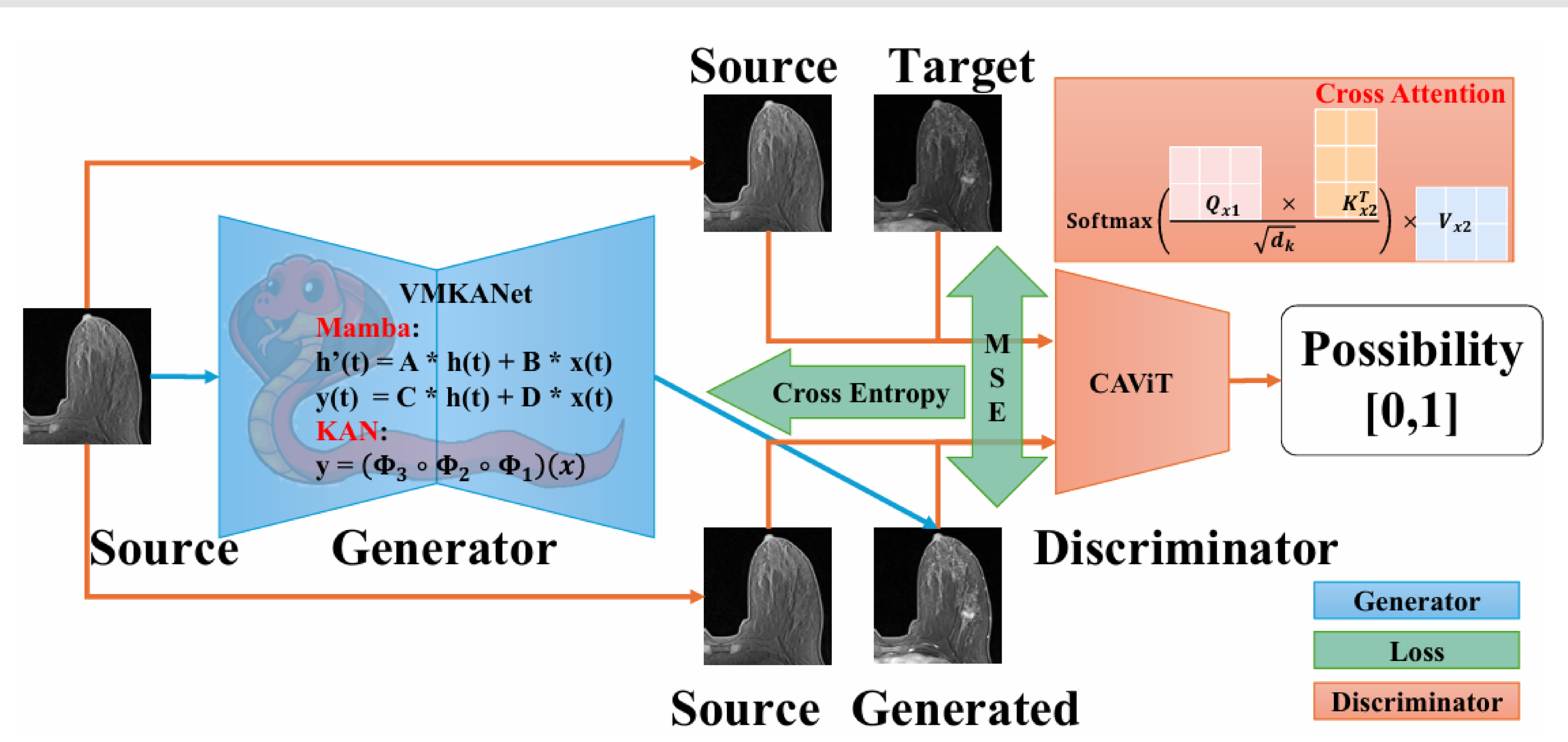
Methodology

Our framework employs a 3D cGAN with two core components:

1. VMKANet Generator:
- **Encoder-decoder architecture** processes 2D slices.
- **VKBlock** uses dual-path **KAN** branches and **SS2D** spatial modeling.
- **KAN** replaces MLPs with spline-based activations for nonlinear mapping.
- **SS2D** scans images in 4 directions and discretizes parameters via state-space models.

2. CAViT Discriminator:
- Twin 3D ViTs with cross-attention between layers.
- Compares (source, target) and (source, generated) pairs via $\mathrm{Softmax}(QK^T/\sqrt{d_k})V$.

Loss Function:
- Generator: **Adversarial loss + MSE** (pixel accuracy).
- Discriminator: **Cross-entropy** loss.



Results

Experiments on ISPY2 dataset (1,000 MRI pairs) demonstrate superior performance:

1. Quantitative Metrics:
- Best **SR (0.9298)** and **SSIM (0.9259)** with VMKANet+CAViT.
- Lowest **NRMSE (0.0397)** and **SMAPE (0.2122)**.

2. Ablation Study:
- KAN + Cross-Attention (CA) boosts SR by 9.8% (Table).
- ViT+CA discriminator improves structural fidelity (Table).

3. Qualitative Analysis:
- Enhanced vascular details and tumor contrast.
- Minimal artifacts in generated images.

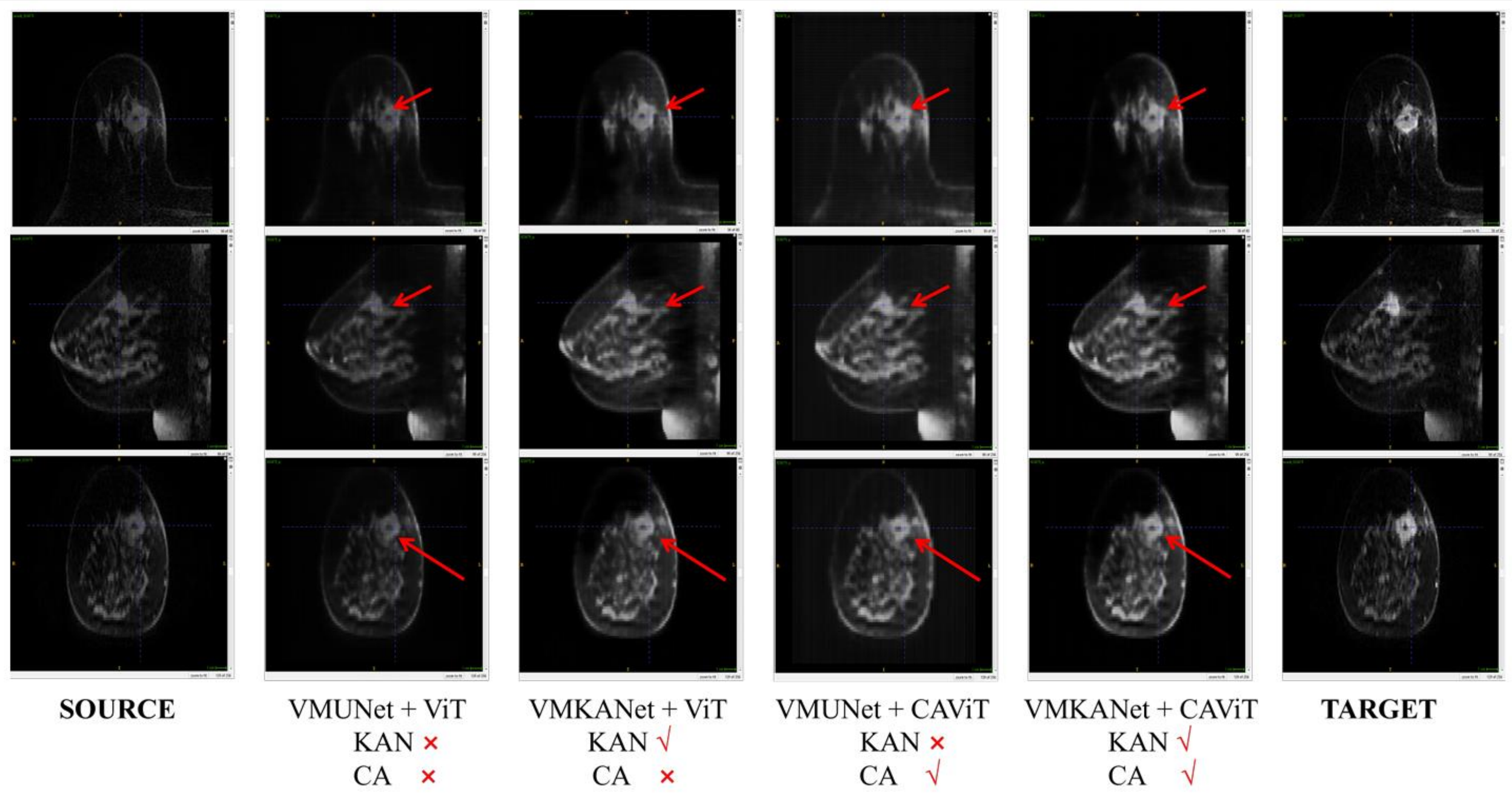


Table : Ablation Study Results. RGB indicate the Top 3.

MODEL	KAN	CA	SR ↑	SSIM ↑	MI ↑	NRMSE ↓	SMAPE ↓
model1			0.8459 ± 0.0586	0.7265 ± 0.1596	0.2815 ± 0.1672	0.4053 ± 0.2819	0.3913 ± 0.0918
model2	✓		0.8523 ± 0.0447	0.8317 ± 0.0961	0.3803 ± 0.1842	0.1159 ± 0.0808	0.2823 ± 0.0667
model3		✓	0.8502 ± 0.0591	0.7793 ± 0.1470	0.4158 ± 0.1988	0.0679 ± 0.0367	0.4063 ± 0.1069
model4	✓	✓	**0.9298 ± 0.0287**	**0.9259 ± 0.0465**	**0.4361 ± 0.1788**	**0.0397 ± 0.0207**	**0.2122 ± 0.0667**

Conclusion

Our Mamba-driven cGAN synthesizes high-quality DCE-MRI without contrast agents, combining:
1. **VMKANet (Mamba+KAN)** for efficient feature extraction.
2. **CAViT discriminator with cross-attention** for precise alignment.

Validated on ISPY2 data, it achieves top-tier metrics (SR: 0.9298, NRMSE: 0.0397) and enhances tumor visibility. While limited to 2D processing and single-dataset testing, this work pioneers safer, cost-effective breast MRI, eliminating GBCA risks. Future directions include 3D extension and clinical validation.

Algorithm SSM + KAN Selection (Ours)

Input: $x : (B, L, D)$
Output: $y : (B, L, D)$
1: $A : (D, N) \leftarrow$ Parameter
2: $B : (B, L, N) \leftarrow s_B(x) \leftarrow KAN(x)$
3: $C : (B, L, N) \leftarrow s_C(x) \leftarrow KAN(x)$
4: $\Delta : (B, L, D) \leftarrow \tau_\Delta(\text{Parameter} + s_A(x)) \leftarrow KAN(x)$
5: $\bar{A}, \bar{B} : (B, L, D, N) \leftarrow \text{discretize}(\Delta, A, B)$
6: $y \leftarrow \text{SS2D}(\bar{A}, \bar{B}, C)(x)$ ▷ Time-varying
7: **return** y