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Segmentation with Kaleidoscope Shuffle

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What is Kaleidoscope Transform?

The **Kaleidoscope Transform** is a way to create smaller, down-sampled copies of an image or sequence and keeping important overall information. It does this by rearranging parts of the image or data in a special pattern, which can also help generate fractal-like structures.

Key factors affecting it are:

Downsampling factor (ν): how much the sequence is reduced

Smear factor (σ): controls spacing/interleaving when recombining

Mapping formula:

$$k = \left(\left\lfloor \frac{N}{\nu} \right\rfloor (n \bmod \nu) + \sigma \left\lfloor \frac{n}{\nu} \right\rfloor \right) \bmod N$$

where N is the sequence length.

What is Kaleidoscope Shuffle?

Kaleidoscope Shuffle is a new transform inspired by the Kaleidoscope Transform and its Multiplication variant. It applies dilation factors to scale rows and columns before mapping, allowing for flexible, non-square tilings of images or sequences.

Why developed:

To handle non-square images and create more flexible, smaller models with finer resolution by scaling separately in x and y directions.

Key factors:

Dilation factors (f, g) for scaling rows and columns

Mapping formula (1D):

$$\kappa_{rc}[L_n, \nu, \sigma] = \left(\left\lfloor \frac{N}{\nu} \right\rfloor (L_n \bmod \nu) + \sigma \left\lfloor \frac{L_n}{\nu} \right\rfloor \right) \bmod N$$

where L is replaced by f and g for 2D row and column scaling.

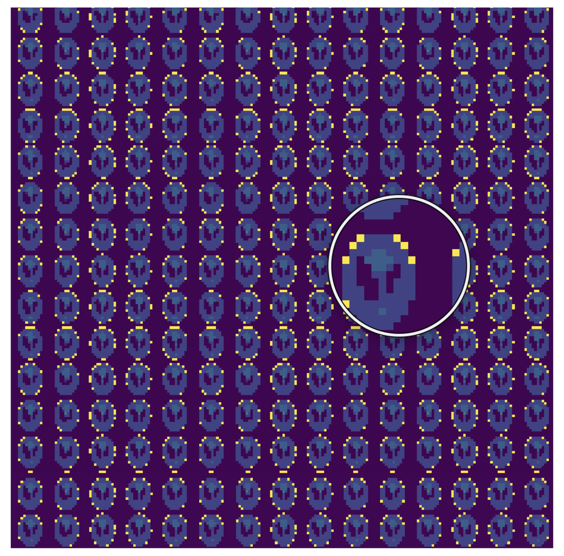

Figure 1. Kaleidoscope Shuffle applied on a 2D image.

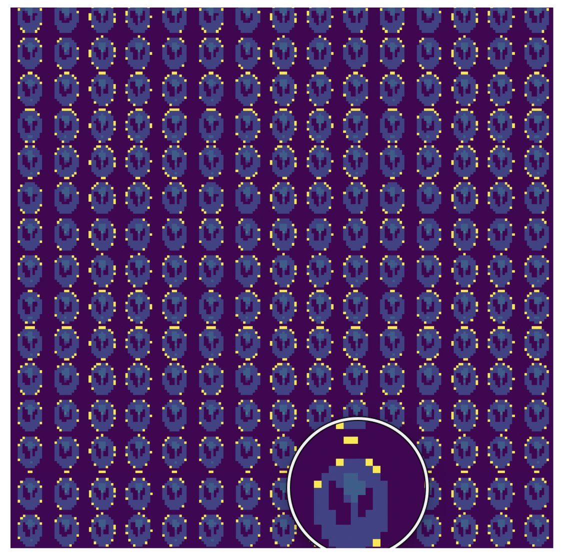

Figure 2. Another perspective of the shuffled output.

AIMS AND OBJECTIVES

Where's the research?

- The Kaleidoscope Shuffle is a novel technique that has seen limited exploration in deep learning for image processing.
- Our research integrates the Kaleidoscope Shuffle into the CAN3D model to explore its effect on 3D image analysis tasks.
- Although improvements were minimal, this work provides valuable insights into the method's practical application and potential.

METHODOLOGY

In this study, the Kaleidoscope Shuffle mechanism was integrated into the CAN3D model to perform semantic segmentation on the OASIS dataset. The key steps include:

- **CAN3D Baseline:** Trained the original model with standard configuration to establish baseline performance.
- **Layer Tweaks:** Replaced ReLU activation with SELU for performance improvement.
- **KT Shuffle Conversion:**
  - Original implementation in PyTorch designed for 2D images (4D tensors).
  - Converted to handle 3D volumes by extending to 5D tensors (with a depth dimension).
  - For an input tensor $X \in \mathbb{R}^{1\times D\times N\times N\times 1}$, the generalized shuffle is defined as:

$$T[d, h, w] = X\left[d,\ \kappa_{\text{rc}}[f \cdot h,\ \nu,\ \sigma],\ \kappa_{\text{rc}}[g \cdot w,\ \nu,\ \sigma]\right]$$

- **TensorFlow Rewrite:** Re-implemented Kaleidoscope Shuffle in TensorFlow to integrate with CAN3D.
- **Parameter Exploration:** Conducted tests using varying values of parameters (N, σ, f, and g) to study their effects on segmentation quality.
- **Integration:** Incorporated KT Shuffle into the training

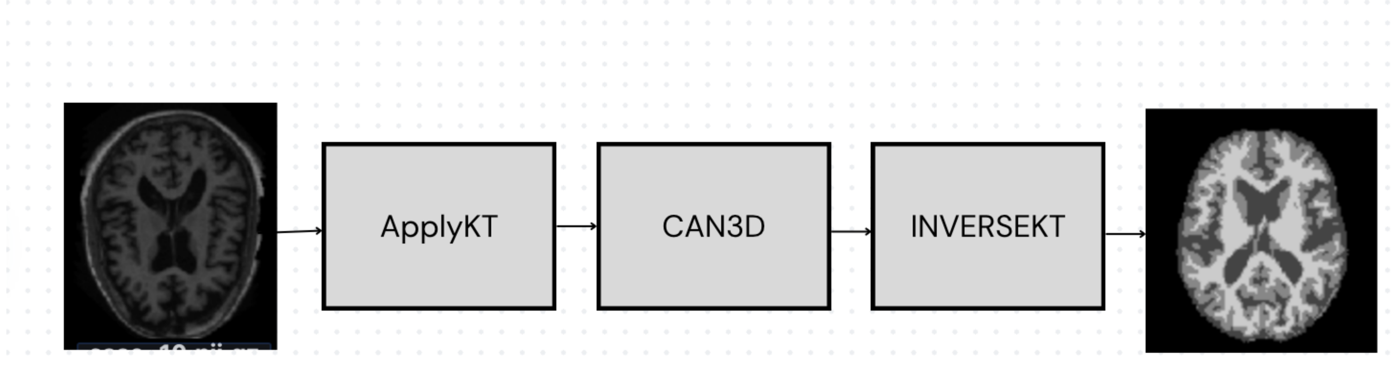

Figure 3. Pipeline showing integration of KT Shuffle into the CAN3D segmentation model.

CAN3D

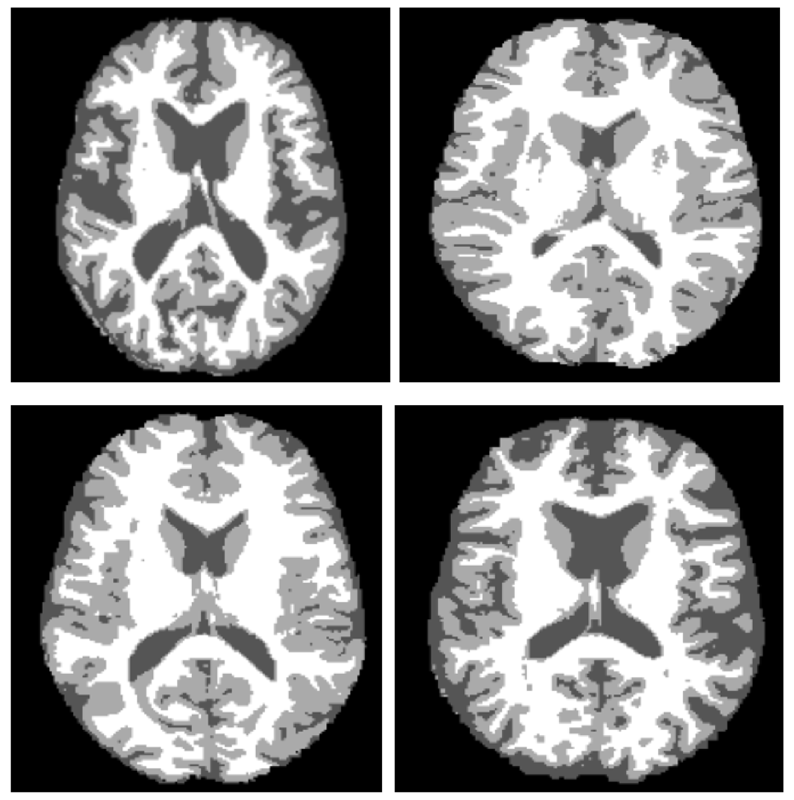

Figure 4. CAN3D Output Results

Result

Baseline **DSC_Seg** rose from **0.62** to **0.95** in 25 epochs; KT Shuffle (**DSC_Seg+KT**) rose slower to **0.69**. Baseline loss (**Loss_Seg**) dropped from **0.39** to **0.055**; KT Shuffle loss (**Loss_Seg+KT**) plateaued near **0.31**.

Figure 5. Losses Comparision

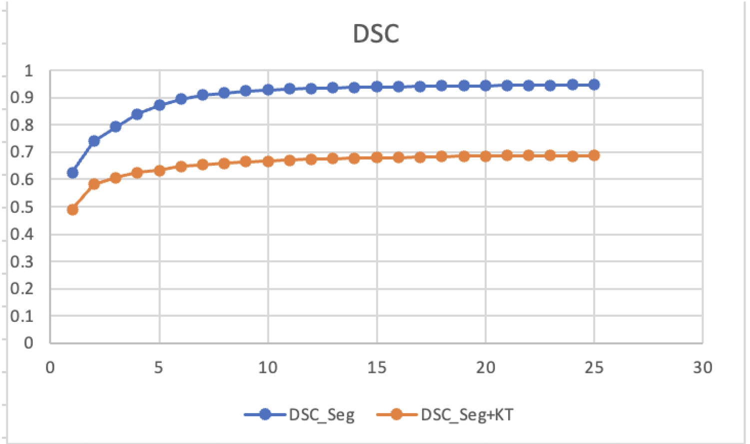

Figure 6. DSC Comparision

Conclusion

- KT Shuffle yielded higher loss than the baseline despite initial expectations.
- This suggests challenges in adapting 2D augmentation methods directly to 3D data.
- Highlights the necessity for more tailored transformation approaches for volumetric data.