

Education



KNUST

KWAME NKRUMAH UNIVERSITY
OF SCIENCE AND TECHNOLOGY

BSc. Biomedical Engineering (2021-2024)



MSE. Data Science

(2025-2026)

Toufiq Musah

toufiqmusah.github.io

Research



KCCR - Centre for Collaborative Research in Tropical Medicine (2024-2025)

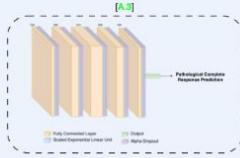


Responsible Artificial Intelligence Lab (2024-2025)

Research Summary

(A) Foundational Machine Learning & Algorithmic Methods

- . A.1 Monte Carlo Dropout for epistemic uncertainty [1]
- . A.2 Deep Ensembles for Robust Generalization [1,3]
- . A.3 Self-Normalizing Networks for Stable Convergence [2]
- . A.4 Label-Masked Elastic Deformation Augmentations [3]



$$\text{ECE} = \sum_{m=1}^M \frac{|B_m|}{N} |\text{acc}(B_m) - \text{conf}(B_m)|$$
$$p(y|x) \approx \frac{1}{K} \sum_{k=1}^K f_{\theta(k)}(x)$$

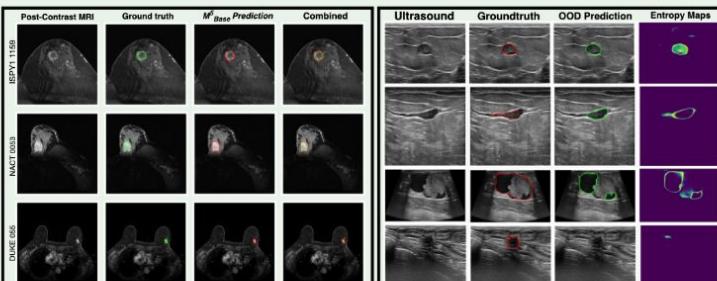
(B) Medical Image Computing and Representation Learning Across Modalities

- . B.1 Breast Tumor Segmentation in Ultrasound
- . B.2 Breast Tumor Segmentation in Dynamic Contrast Enhanced MRI
- . B.3 Pathological Complete Response Assessment using DCE-MRI
- . B.4 Multi-Parametric MRI Brain Tumor Segmentation in the African Context
- . B.5 Ischemic Stroke Lesion Detection in Non-Contrast CT Scans

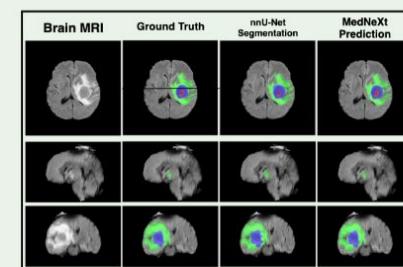
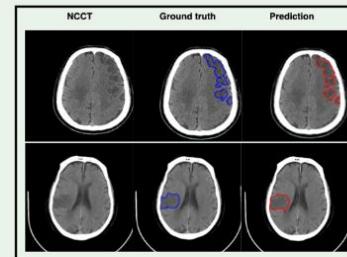


Research
Summary

. C.1 Trustworthy Breast Lesion Delineation and Characterization []



- . C.2 Early Ischemic Stroke Detection from Low-Cost NCCT []
- . C.3 Multi-Region Brain Tumor Monitoring in the Sub-Saharan African Context



(C) Towards Accessible and Reliable Clinical AI Applications

Automated Segmentation of Ischemic Stroke Lesions in Non-Contrast Computed Tomography Scans

MICCAI'24 – Workshop Paper

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Automated Segmentation of Ischemic Stroke Lesions in Non-contrast Computed Tomography Images for Enhanced Treatment and Prognosis

Conference paper | First Online: 09 February 2025
pp 73–80 | [Cite this conference paper](#)

Toufiq Musah , Prince Ebenezer Adjei & Kojo Obed Otoo

 Part of the book series: [Communications in Computer and Information Science \(\(CCIS, volume 2240\)\)](#)

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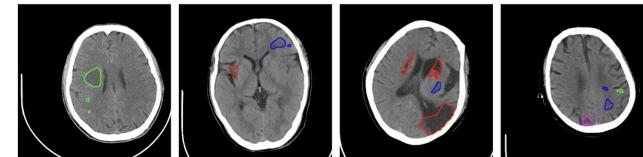
310 Accesses 2 Citations

Problem:

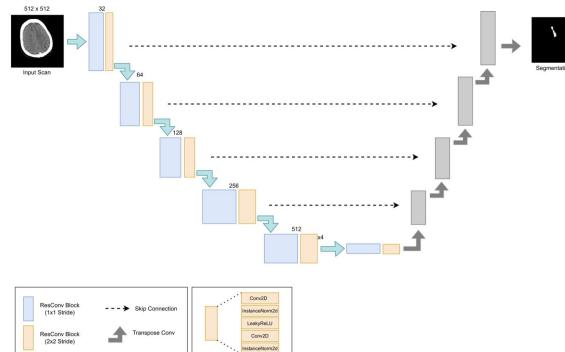
Early Ischemic Stroke detection via neuroimaging is usually done using **DWI MRI**. MRI is not a widely accessible neuroimaging modality in underserved region.

Can we perform IS detection using NCCTs
(More widely available and accessible)

1. NCCT Dataset of Different Infarct Types



2. Residual-Encoder U-Net in nnU-Net Framework



Method:

NCCTs are labeled using DWI pairs.
Preprocess NCCTs into relevant slices.

Using a well-validated biomedical image segmentation framework (nnU-Net), with a **Residual-Encoder U-Net**, we perform segmentation of acute infarcts in NCCTs.

Automated Segmentation of Ischemic Stroke Lesions in Non-Contrast Computed Tomography Scans

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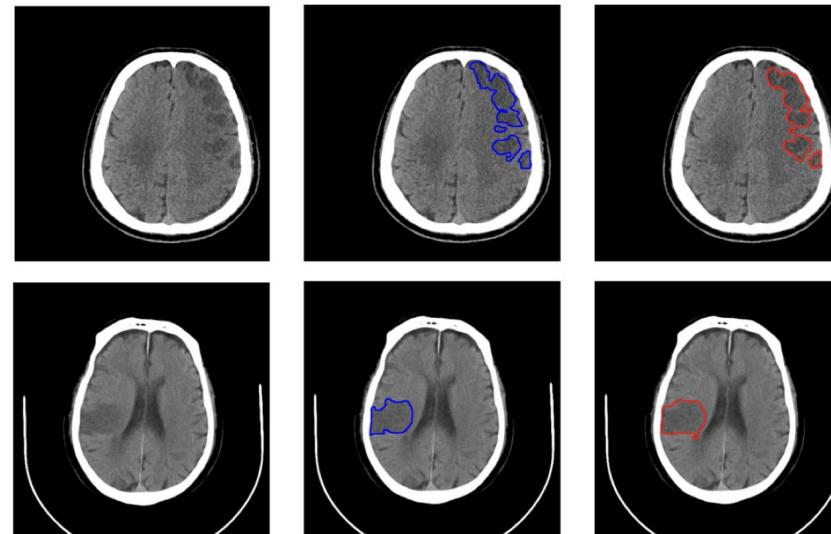
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Result:

Achieved 0.752 Dice in the best when adjusting for outliers.

Comparative works achieved 0.578 Dice.

3. Results from Segmenting Acute Infarcts (0.75 Dice – Benchmark 0.57)



Tumor Segmentation in Dynamic Contrast MRI | Radiomics-Based Pathological Complete Response Assessment

MICCAI'25 – Deep-Breath

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Large Kernel MedNeXt for Breast Tumor Segmentation and Self-normalizing Network for pCR Classification in Magnetic Resonance Images

Conference paper | First Online: 21 September 2025
pp 72–80 | Cite this conference paper

Toufiq Musah 

 Part of the book series: [Lecture Notes in Computer Science \(\(LNCS, volume 16142\)\)](#)

 Included in the following conference series:
[Deep Breast Workshop on AI and Imaging for Diagnostic and Treatment Challenges in Breast Care](#)

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Tumor Segmentation in Dynamic Contrast MRI | Radiomics-Based Pathological Complete Response Assessment

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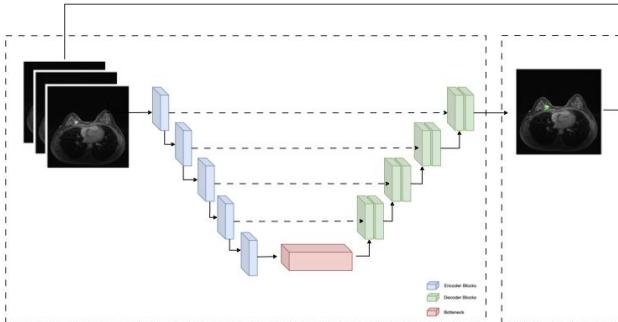
138 Accesses

Problem:

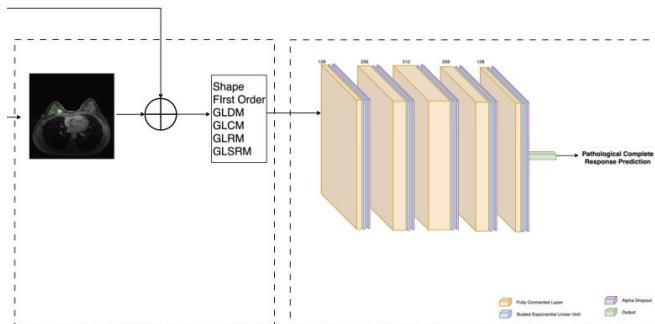
Accurate breast tumor segmentation in DCE-MRI is important for downstream tasks.

There is a need to capture both the subtle enhancement patterns of tumors across contrast time points and the broader breast tissue context, which larger receptive fields naturally accommodate.

1. Segmenting Tumors w/ Large Kernel Network



2. Assessing pCR w/ Radiomics-Based SNN



Method:

A large-kernel MedNeXt architecture with a two-stage training strategy that expands the receptive field from 3^3 to 5^3 kernel sizes using the UpKern algorithm.

This allowed for stable transfer of learned features to larger kernels, improving segmentation performance

Tumor Segmentation in Dynamic Contrast MRI | Radiomics-Based Pathological Complete Response Assessment

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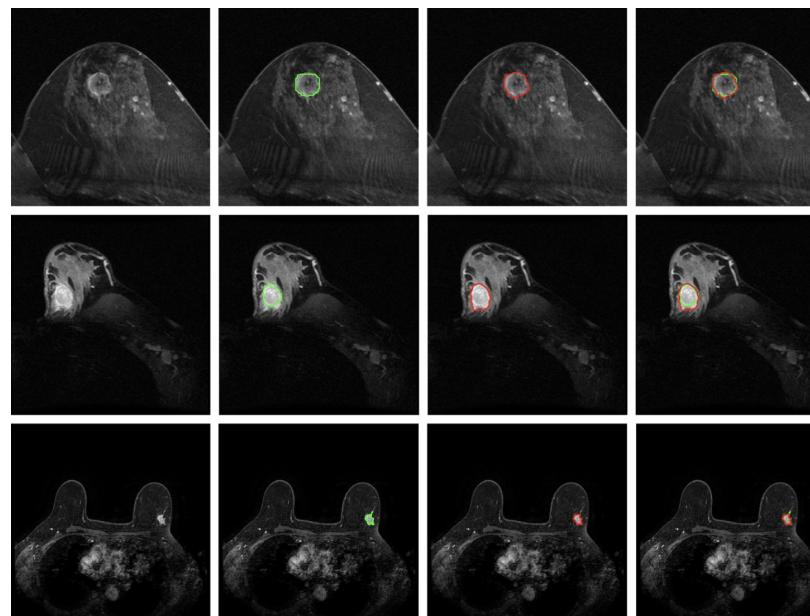
138 Accesses

Result:

Ensemble of large-kernel networks achieved a **Dice of 0.67** and a **NormHD of 0.24**.

For pCR classification, a self-normalizing network (SNN) on radiomic features achieved an accuracy of **57%**, and up to **75%** in some subgroups.

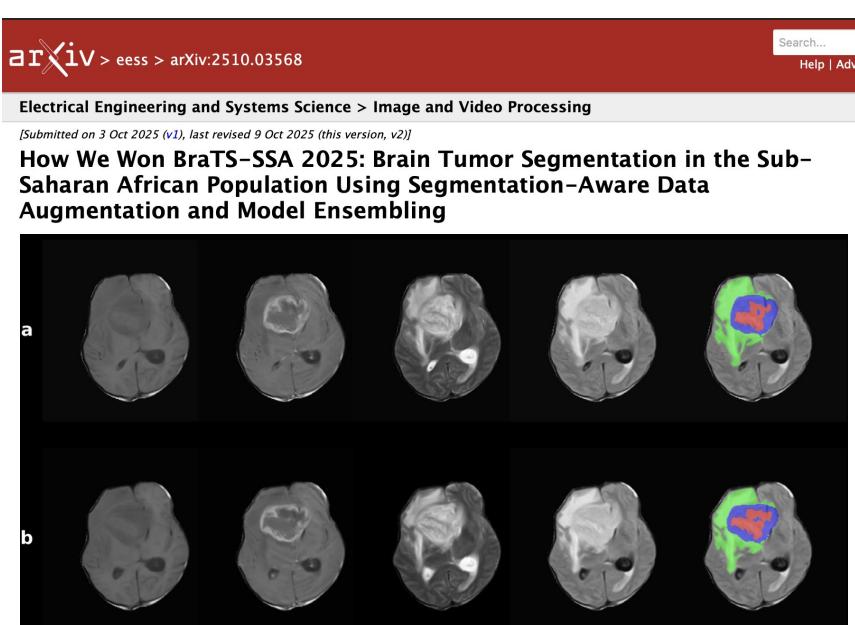
3. 0.67 Dice | 64M Parameters – vs – 0.65 | 700M Benchmark



Other Works

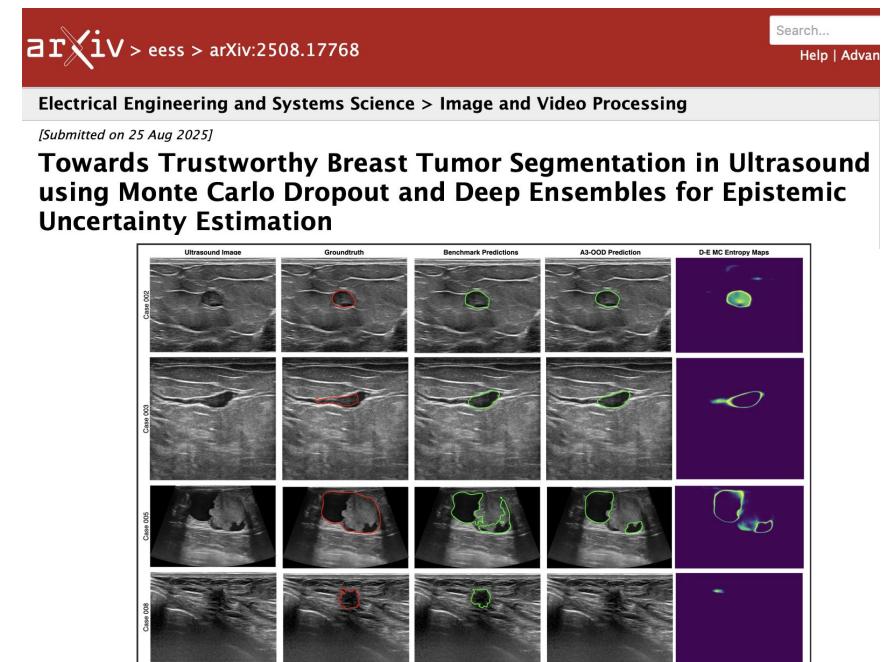
First Place Submission: Brain Tumor Segmentation Challenge (2025)

Performed segmentation-aware data augmentation with controlled rigorous elastic deformations, and model deep-ensembling for SOTA segmentation performance ..



Oral presentation at MICCAI MIRASOL Workshop on trustworthy segmentation in ultrasound.

Performed epistemic uncertainty estimation in segmentation using Deep Ensembling and Monte Carlo dropout .



Current Work – ULF-BrainGen: Physics-Guided Generative Synthesis and Super-Resolution of Ultra Low-Field MRI

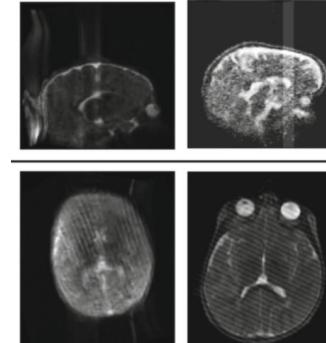
Funded By:

The African Network for Artificial Intelligence in Biomedical Imaging



Problem:

Ultra low-field MRI presents a great opportunity for expanding access to MRI procedures in underserved regions of the world.

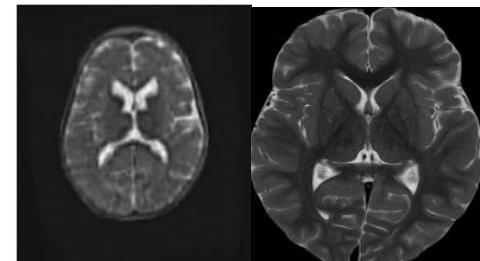


The imaging quality due to inherent noise and low magnetic strength sometimes leads to poor imaging quality.

Proposal:

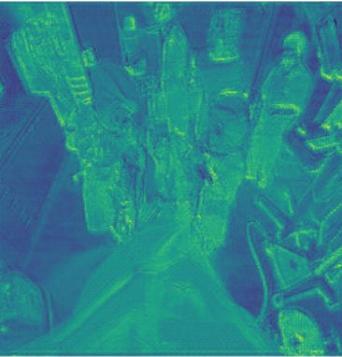
ULF-BrainGEN is a physics-guided generative modeling framework designed to synthesize ULF-MRI scans into diagnostically faithful, high-quality images comparable to conventional 1.5 T MRI systems.

By quantifying ULF degradation patterns and making use of state-of-the-art generative architectures explicitly guided by MRI physics.



Projects

Surgical Video Scene Understanding & Panoptic Segmentation



Problem:

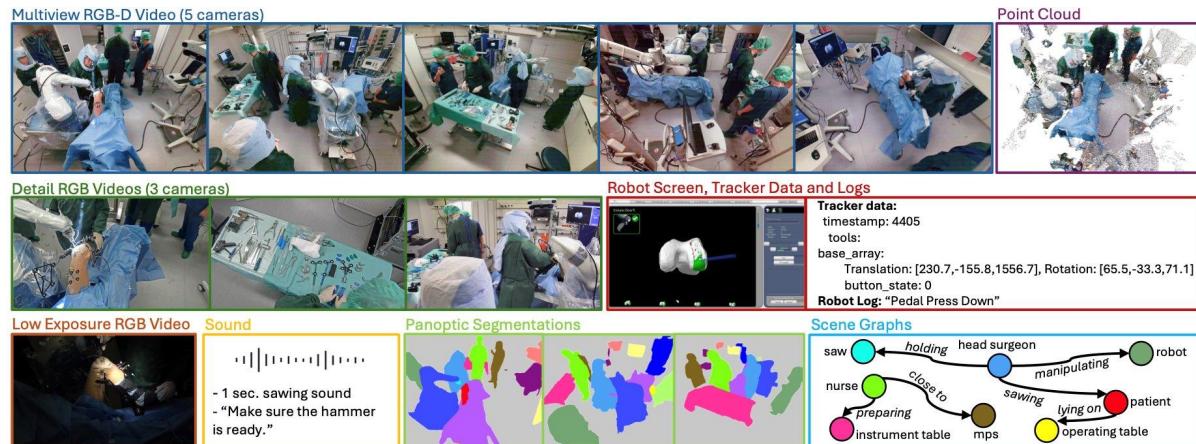
Surgical Operating Rooms are a complex, high-risk environment ...

Precise understanding of interactions among staff, tools, and equipment can enhance surgical assistance and situational awareness

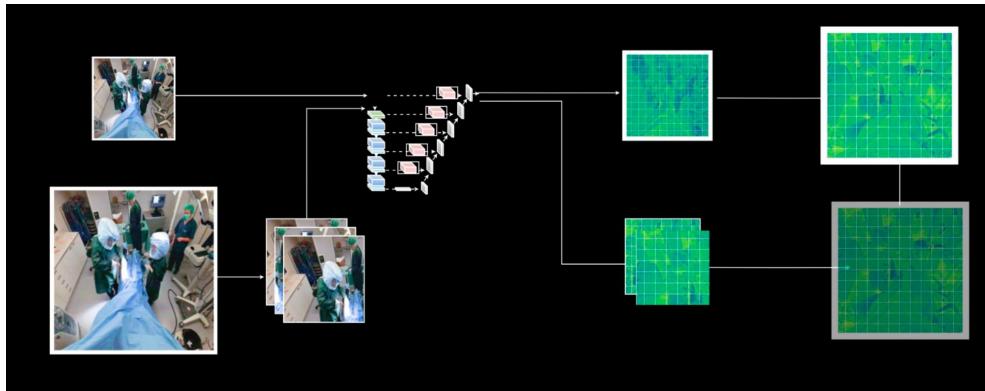
Dataset:

MM-OR dataset including a rich set of synchronized data sources:

- Multi-view RGB-D Video
- Detail RGB Cameras (3 cameras)
- Low-exposure RGB Video
- Audio + Speech Transcripts



Surgical Video Scene Understanding & Panoptic Segmentation



Methods – Panoptic Scene Segmentation:

Applied S2-Scaling to SwinUNETR to enable better feature extraction for high precision segmentation.

Segmented for 21 classes, including personnel and tools.

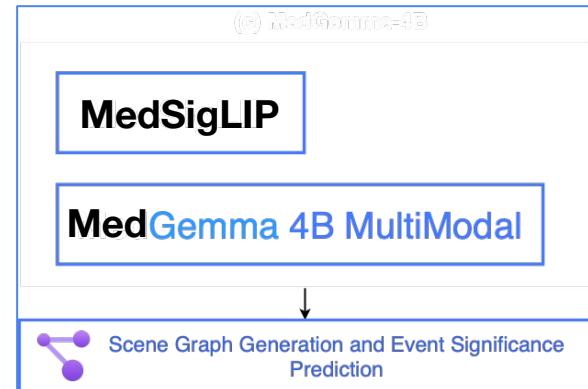


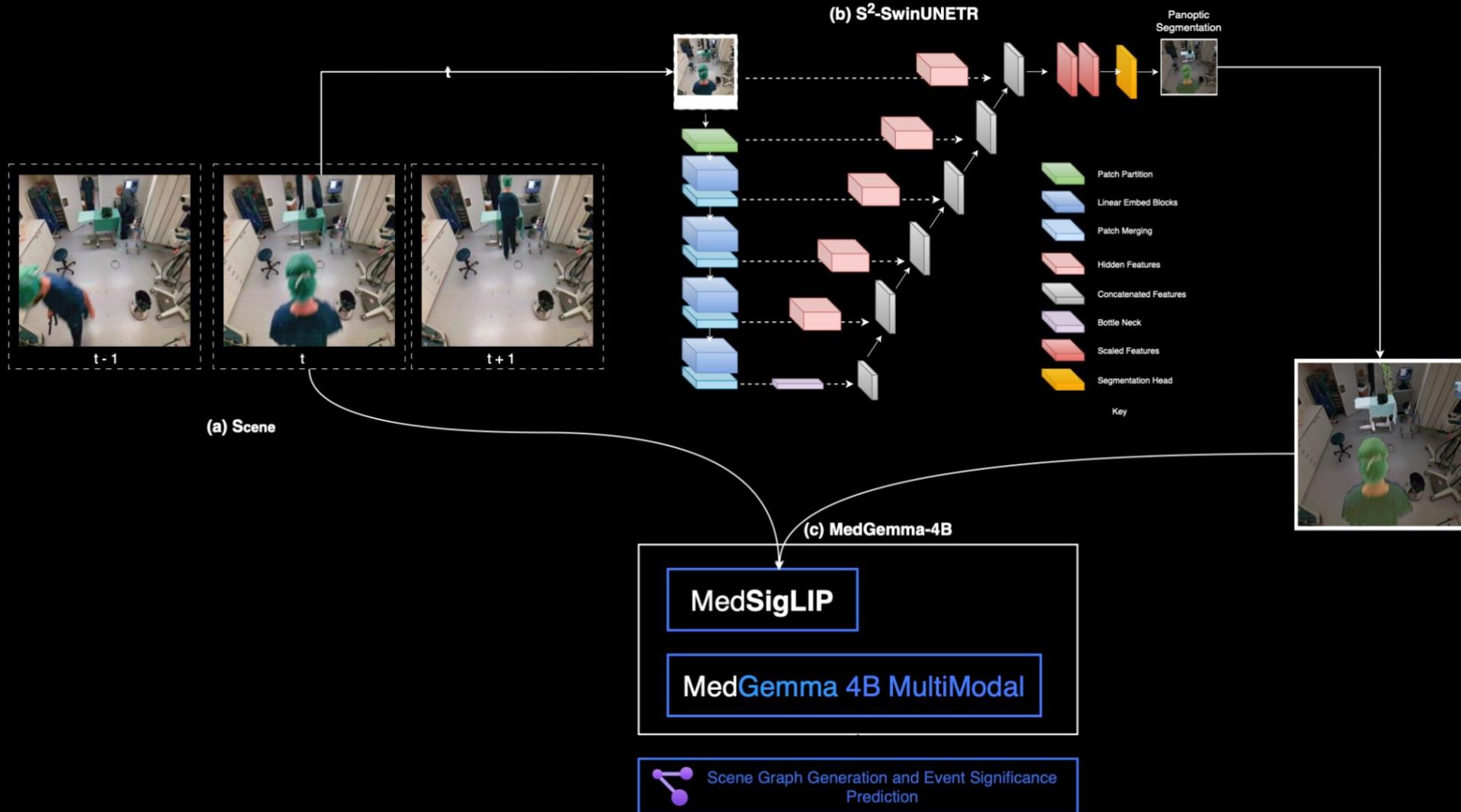
Method – Vision Language Finetuning:

MedGemma Vision Language model for Scene Graph Generation and Event Significance Classification.

Model trained on 3 FPS surgical video + panoptic segmentations.

Trained with Quantized Low-Rank Adaptation.

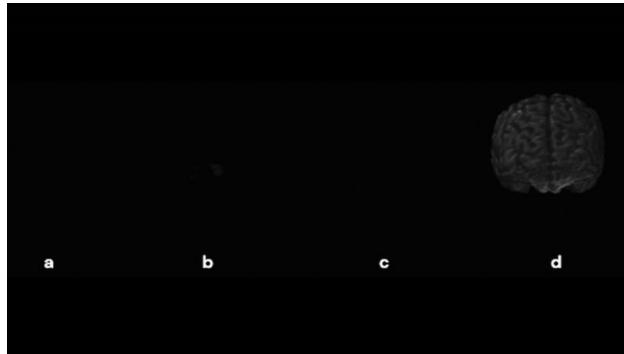




Tutorial Articles on 3D Medical Image Computing

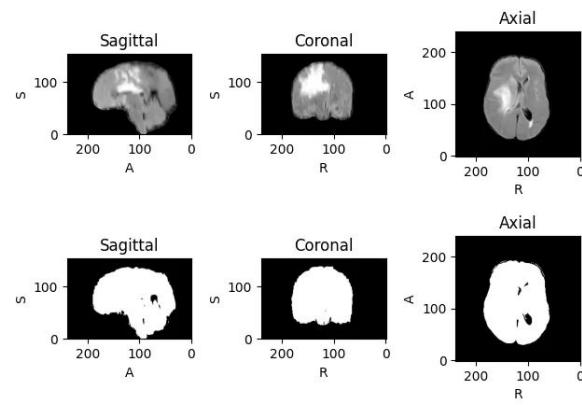
A Hitchhiker's Guide to 3D Medical Image Processing (Preprocessing, Augmentations & DataLoader)

 Toufiq Musah · 10 min read · Aug 17, 2025



Introduction to TorchIO for 3D MRI Processing: Preprocessing Transforms (Part 1)

 Toufiq Musah · 7 min read · Feb 2, 2025



Introduction to TorchIO for 3D MRI Processing: Augmentation Transforms & DataLoaders (Part 2)

 Toufiq Musah · 6 min read · May 11, 2025



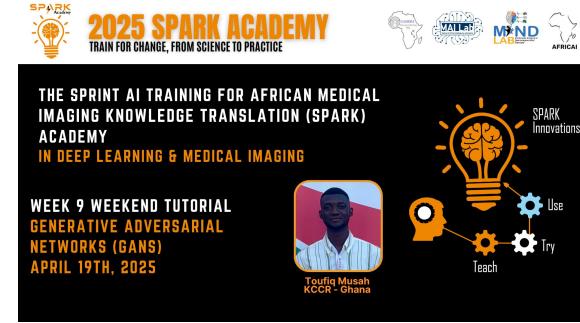


SPARK ACADEMY

Train the trainer strategy



SPARK ACADEMY – Coordination



Medical Image Segmentation Using MedNeXt. The video shows a Jupyter Notebook interface with a diagram of the MedNeXt architecture. The diagram illustrates a U-shaped encoder-decoder structure with skip connections. The encoder consists of multiple residual blocks, each containing a residual connection and a layer normalization block. The decoder consists of a series of upsample blocks, each followed by a residual block. The overall flow is from input image to segmentation output. A video player interface is visible at the bottom, showing the video title and a play button.

How we won BraTS 2023 Adult Glioma challenge? Just faking it! Enhanced Synthetic Data Augmentation and Model Ensemble for brain tumour segmentation. The video shows a diagram of the training pipeline for the GHGAN. It starts with an "Input conditioned by label" (y) and a "Noise scan (z)". These are concatenated and fed into a generator (G) to produce a "Synthetic Volumetric scan ($G(z|y)$)". This synthetic scan is then processed by a discriminator (D) along with a "Real Volumetric scan (x)" to determine if it is "Real? Fake?". A video player interface is visible at the bottom, showing the video title and a play button.

Other Ongoing Works ...

MedSegMNIST – A Python Library for Easy Access to 2D/3D Medical Image Segmentation Datasets for Benchmarking and Learning Purposes.

MED-RAE – Representational AutoEncoders for Medical Image Synthesis ...

SSC-UNet – State-Space ConvNeXt UNet for 3D Biomedical Image Segmentation

Topology-Based Network Optimization for Neuro Tracting/Segmentation

Imaging-Biomarker Based Prediction