EXPLORING 3D DEEP LEARNING-BASED CLASSIFICATION OF HEAD CT SINOGRAMS TO BYPASS IMAGE RECONSTRUCTION

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Introduction

Computed tomography (CT) is vital to image-based diagnostics; however, conventional analysis relies upon the computationally intensive reconstruction process of raw projection data (sinograms) into human-interpretable images. While essential for visualization purposes, reconstruction carries the potential to introduce artifacts, distort quantitative biomarkers, and incur additional computational overhead. Advancements in deep and machine learning have opened up the possibility that sinogram data is sufficient for classification, eliminating the need for reconstruction entirely. As such, this Signature Work aims to explore 3-dimensional deep learning-based classification directly via head CT sinograms as a means of improving diagnostic efficiency and possibly enabling resource-limited hospitals to deploy AI more effectively.

Materials & Methods

Stanford-SinoCT Dataset

- 9,779 non-contrast head CT studies (GE Scanner)
- Each includes *paired reconstructed volume and stimulated sinogram*
- Labels: *Normal* or *Abnormal* (radiologist verified) GE scanner
- Pixel spacing: 0.49 - 0.60 mm

Hardware & Software

- Duke GPU Medical Research Server
- NVIDIA A40 GPU (47.7 GB VRAM)
- 34-core x86-64 CPU, 67.1 GB RAM
- Python 3.12 | PyTorch 2.2.1

Pre-Processing

- Resized input volumes to (192 x 192 x 96)
- Standardized intensities, normalized per scan
- Split: 70% Train | 15% Val | 15% Test (patient-level separation)

Model Architectures

- Identical 3D ResNet-18 Architectures for sinogram & image domains
- Derived from Torchvision CNN library
- Compared to DenseNet3D, EfficientNet3D, MobileNet3D on Sinogram Data
- Trained 20 epochs | weighted cross-entropy loss

Training Procedure

- Identical ResNet3D architectures per domain
- ADAM (lr = 1e-4, batch = 8, weight decay = 1e-5)
- Weighted cross-entropy for class imbalance
- Early stopping (patience = 5) | AMP enabled

Evaluation Metrics

- AUROC | AUPRC | Accuracy | Precision | Recall | F1-Score
- 95% Confidence Intervals (CIs) & p-values reported
- ROC & PR curves visualized with normalized radar comparison

Calibration

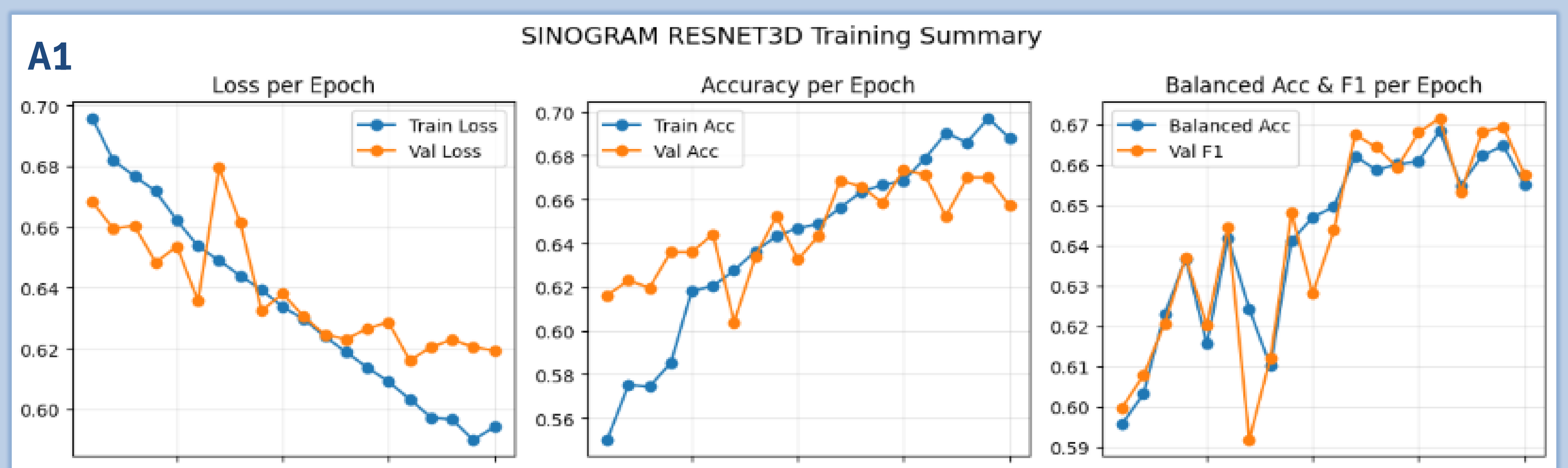
- Post-hoc temperature scaling (validation set)
- Evaluated via ECE & Brier Score for probability reliability

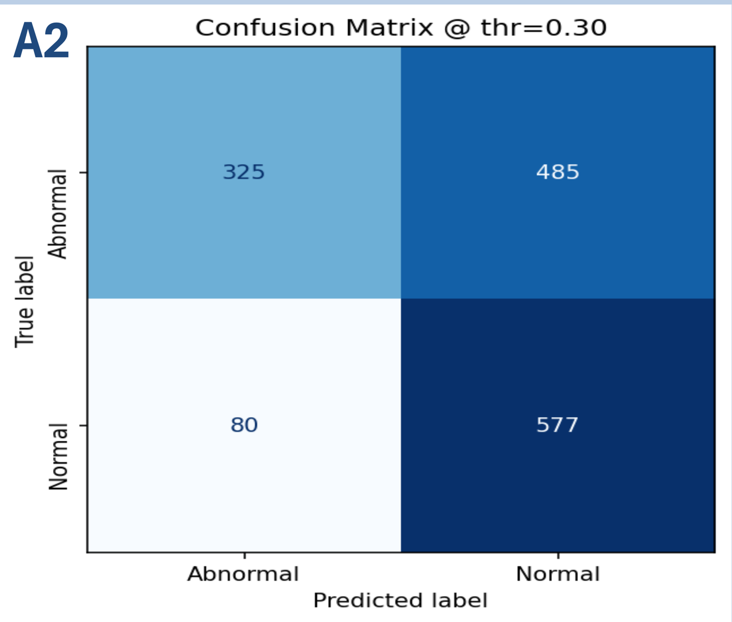
Computational Analysis

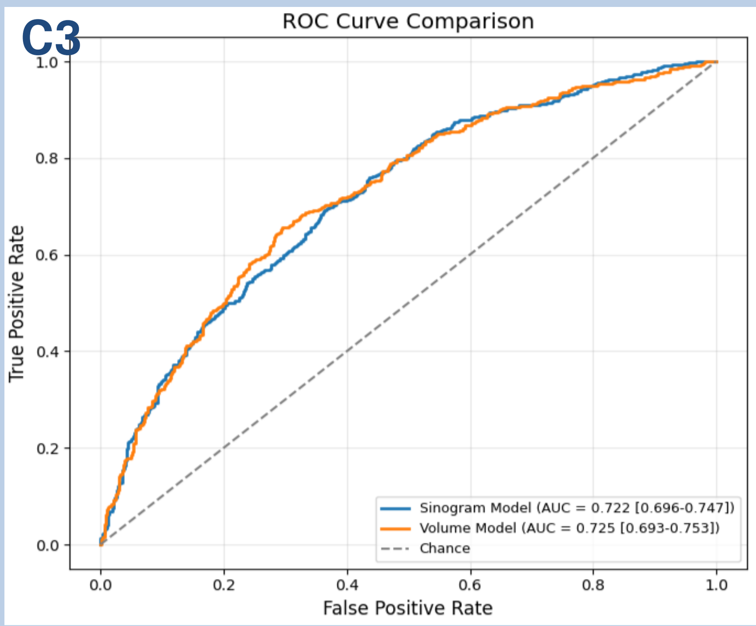
- FLOPS, GPU memory utilization, & average inference time per batch
- Compared between sinogram & volume models

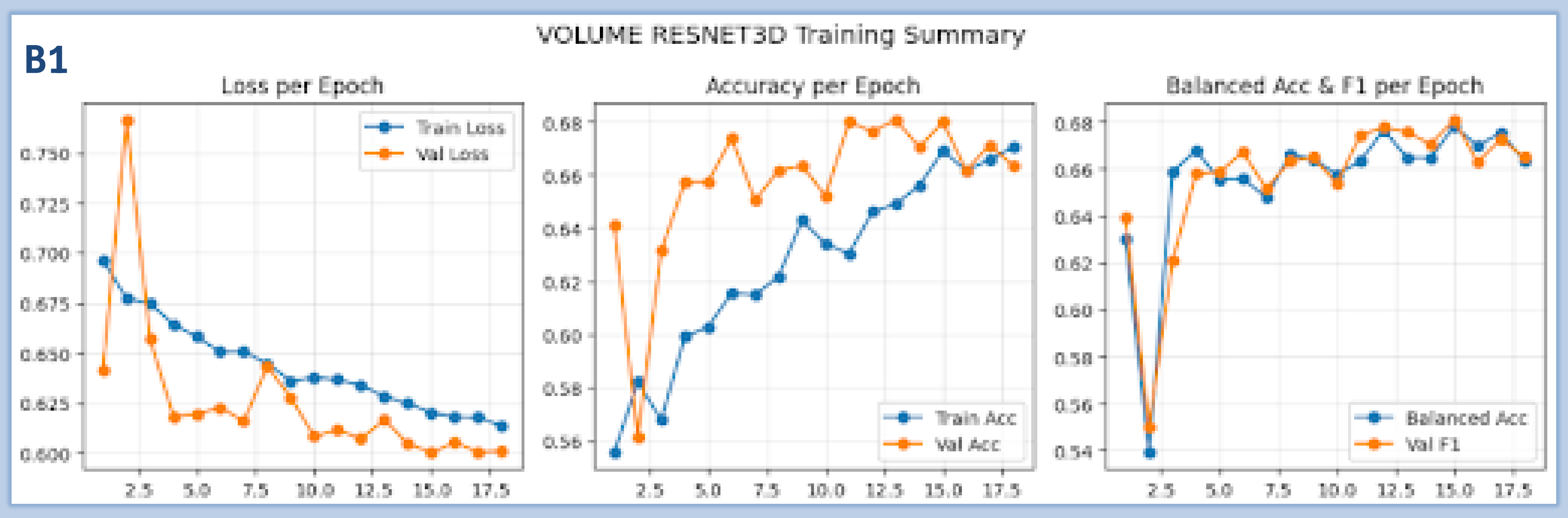
Results

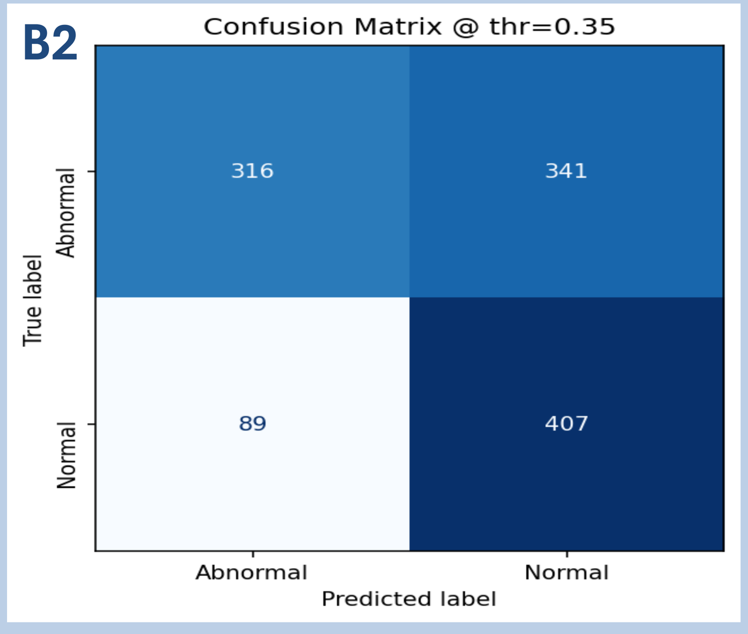
A – Sinogram Model, B – Volume Model, C – ROC, D – PR, 1 – Training Summary, 2 – Performance Confusion Matrix, 3 – Curve Comparison

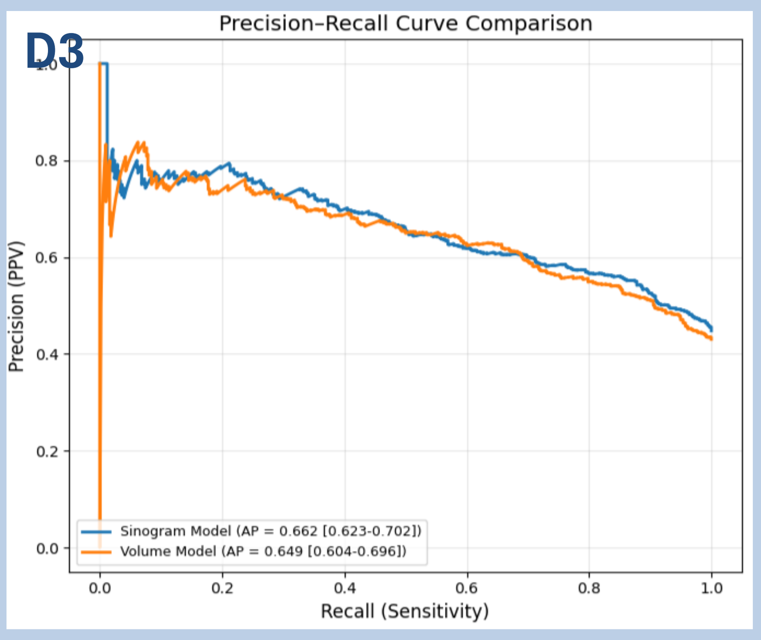












Model	Input	Parameters (M)	FLOPs (G)	Avg. Time (s)	Memory (MB)	Relative Speed	Relative FLOPs
Sinogram 3D ResNet	1 x 192 x 192 x 96	33.16	11.38	0.0032	1279.6	100 %	100 %
Volume 3D ResNet	1 x 192 x 192 x 96	33.16	11.38	0.0033	1197.2	97 %	100 %

Model	Calibration Stage	ECE	Brier Score
Sinogram	Pre- Temp. Scaling	0.0468	0.2130
Sinogram	Post- Temp. Scaling	0.0467	0.2119
Volume	Pre- Temp. Scaling	0.0419	0.2093
Volume	Post-Temp. Scaling	0.0382	0.2094

Discussion

These results demonstrate that direct classification of head CT sinogram data using a 3D ResNet architecture achieves diagnostic performance comparable to that of reconstructed image-domain models (AUROC = 0.721 vs. 0.726). Results confirm that diagnostic information is inherently present and learnable in the projection domain. Statistical testing ($p > 0.5$) indicates no significant difference between classification in either domain, and calibration analysis confirmed stable probabilities. Computationally, both domains showed negligible differences in inference time (~0.003s) and memory load (~12GB), highlighting that sinogram-based learning does not increase computational cost.

Since reconstruction has the potential to introduce artifacts such as streaks and spatial noise, sinogram-based classification minimizes their propagation downstream to diagnostic phases, thereby improving robustness to acquisition variability. Clinically, removing the reconstruction stage can accelerate diagnostic workflows and reduce hardware and energy demands, particularly in high-throughput or resource-limited settings.

Limitations

- Dataset is from a single institution and uses a single scanner manufacturer (GE) and a uniform acquisition protocol, which may reduce generalizability
- Since dataset diversity is limited, multi-center validation is necessary for application
- Models may learn scanner- or protocol-specific characteristics rather than diagnostic features due to varying sinogram statistics resulting from detector geometries & filtration methods
- Binary "normal vs. abnormal" labeling oversimplifies diagnostic complexity and masks disorder-specific performance
- Resizing for comparison purposes during pre-processing might affect the accuracy of CNN classification models by compressing data
- Further analysis required for application assessment toward different classification subtypes

Conclusion

Direct sinogram-domain learning enables comparable diagnostic accuracy to image-based models while eliminating the need for image reconstruction. While this approach does not directly reduce computational overhead with respect to classification, simplification of the pipeline reduces it with respect to reconstruction and simultaneously avoids artifact propagation. As a result, this opens up opportunities for faster triage, reduced hardware dependency, and more accessible AI-assisted CT diagnostics. Industry can also leverage this to develop CT systems that produce AI-ready sinograms and perform real-time sinogram-based triage.

Future Work

Expand to :

- Multi-center datasets and multi-class diagnostic tasks
- Radiomic feature extraction directly from projection data to evaluate reconstruction-free quantitative image biomarker preservation

Clinical Application Requires:

- Multi-institutional testing to ensure diagnostic safety & reproducibility

Could enable:

- Real-time AI triage in emergency- & tele-medicine
- Efficient CT analysis in low-resource/bandwidth-constrained environments

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References

[1] Stanford University Center for Artificial Intelligence in Medicine & Imaging. "SinoCT Dataset," Stanford University, Stanford, CA, USA, 2023. DOI: 10.71718/6tfs-tm78.

[2] S. M. Hooper, J. A. Dunnmon, M. P. Lungren, D. Mastrodicasa, D. L. Rubin, C. Ré, A. Wang, and B. N. Patel, "Impact of upstream medical image processing on downstream performance of a head CT triage neural network," Radiology: Artificial Intelligence, vol. 3, no. 4, e200229, 2021. DOI: 10.1148/ryai.2021200229.

GitHub Repository