Improving Proton Beam Radiotherapy by Sequencing Simulated Patient Data in Compton Camera Real-Time Imaging with Neural Networks

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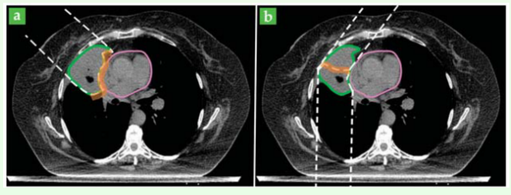
Proton Beam Therapy

Proton beam radiotherapy is an advanced cancer treatment technique utilizing high-energy protons to destroy tumor matter. When the proton beam interacts with patient matter, prompt gamma rays are emitted and then captured in various scatterings by a Compton camera to reconstruct an image of the beam path for use by physicians.

Treatment table at the Maryland Proton Treatment Center.

However, image reconstruction of the beam path is plagued by **mischaracterized scattering sequences** and thus **excessive image noise.** To address this, **machine learning models were developed to classify the scatter data**, which was a novel simulation from CT scans through Geant4 and Monte Carlo with Detector Effects (MCDE) software.



a: Optimal proton treatment beam, (dashed) targeting a tumor (green) with safety margin (orange) that overlaps with critical heart tissue (magenta), **b**: Suboptimal treatment plan of two beams

Data Generation

Multiple novel simulated patient datasets from variable density patient tissue measurements of Duke University CT scans were generated using Geant4 and MCDE. All datasets are 15 columns with 13 classes.

1. **1.1 Million Row Simulated Patient**: MCDE was run on all energy layers separately
2. **4.1 Million Row Simulated Patient**: MCDE was run on all energy layers combined

Class	Interaction 1				Interaction 2				Interaction 3			
123	e_1	x_1	y_1	z_1	e_2	x_2	y_2	z_2	e_3	x_3	y_3	z_3
132	e_1	x_1	y_1	z_1	e_3	x_3	y_3	z_3	e_2	x_2	y_2	z_2
213	e_2	x_2	y_2	z_2	e_1	x_1	y_1	z_1	e_3	x_3	y_3	z_3
231	e_2	x_2	y_2	z_2	e_3	x_3	y_3	z_3	e_1	x_1	y_1	z_1
312	e_3	x_3	y_3	z_3	e_1	x_1	y_1	z_1	e_2	x_2	y_2	z_2
321	e_3	x_3	y_3	z_3	e_2	x_2	y_2	z_2	e_1	x_1	y_1	z_1
124	e_1	x_1	y_1	z_1	e_2	x_2	y_2	z_2	single			
214	e_2	x_2	y_2	z_2	e_1	x_1	y_1	z_1	single			
134	e_1	x_1	y_1	z_1	single				e_2	x_2	y_2	z_2
314	e_2	x_2	y_2	z_2	single				e_1	x_1	y_1	z_1
234	single				e_1	x_1	y_1	z_1	e_2	x_2	y_2	z_2
324	single				e_2	x_2	y_2	z_2	e_1	x_1	y_1	z_1
444	single				single				single			

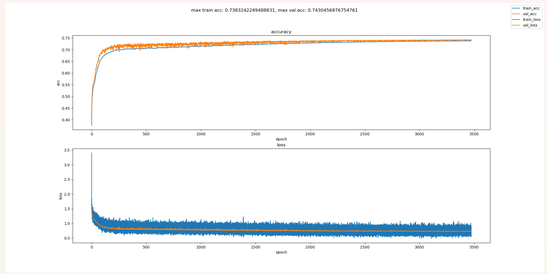
Machine Learning

- Implemented multiple PyTorch ML models including Long Short-Term Memory (LSTM), Fully-Connected Neural Network (FCN), 1D Convolutional Neural Network (CNN), and Transformer Network
- Performed hyperparameter tuning through grid search using the BRIDE coding platform from [3]
- Trained on multiple GPUs

Results

4.1 Million Row Data Results

- Best FCN model achieved 74% training accuracy and 74.2% testing accuracy.

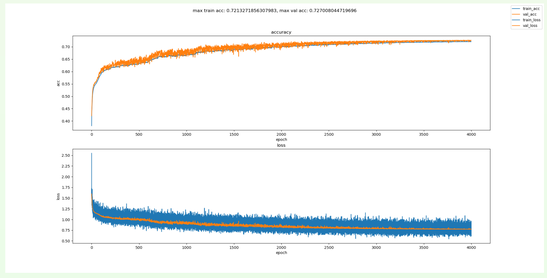


Accuracy and loss curves over epochs of best FCN model.

- Best LSTM model achieved 74.5% training and 73.5% testing accuracy.
- Best Transformer Model achieved 75% training and 70% testing accuracy.

1.1 Million Row Data Results

- Best FCN model achieved 72% training and 73% testing accuracy.



Accuracy and loss curves over epochs of best FCN model.

- Best LSTM model achieved 73% training and 70% testing accuracy.
- Best CNN model achieved 80% training accuracy and 50% testing accuracy.

Conclusions

- **Generated much larger simulated patient datasets** of 2x and 4x the size of those used in previous work [3]
- Achieved **large increases in testing accuracy** (up to 18%) from any previous work on patient data [3]
- Best FCN model achieved 74% training and 74% testing accuracy
- Made ML models more robust and reduced overfitting, greatly **improving model generalizability** for use on a real-world clinical setting

UMBC HPCF

This work used the UMBC High Performance Computing Facility (HPCF).

- GPU portion of Chip cluster: 25 GPU nodes containing a total of 148 GPUs

Most Recent References

[1] Jin, Pathak, Calingo, Gautam, Zhao, et al., tech. rep. HPCF–2025–5, 2025.

[2] Jin, Pathak, Calingo, Gautam, Zhao, et al., REU Symposium, *ICDM 2025*, 2025.

[3] Chen, Hodge, Jin, Protz, Wong, et al., *IEEE Big Data 2024*, 2024.

Acknowledgments

- NSF (Big Data REU Site), NIH
- HPCF: NIH, NSF, CIRC, UMBC