Lossless Compression for Volumetric Medical Images Using Deep Neural Network with Local Sampling

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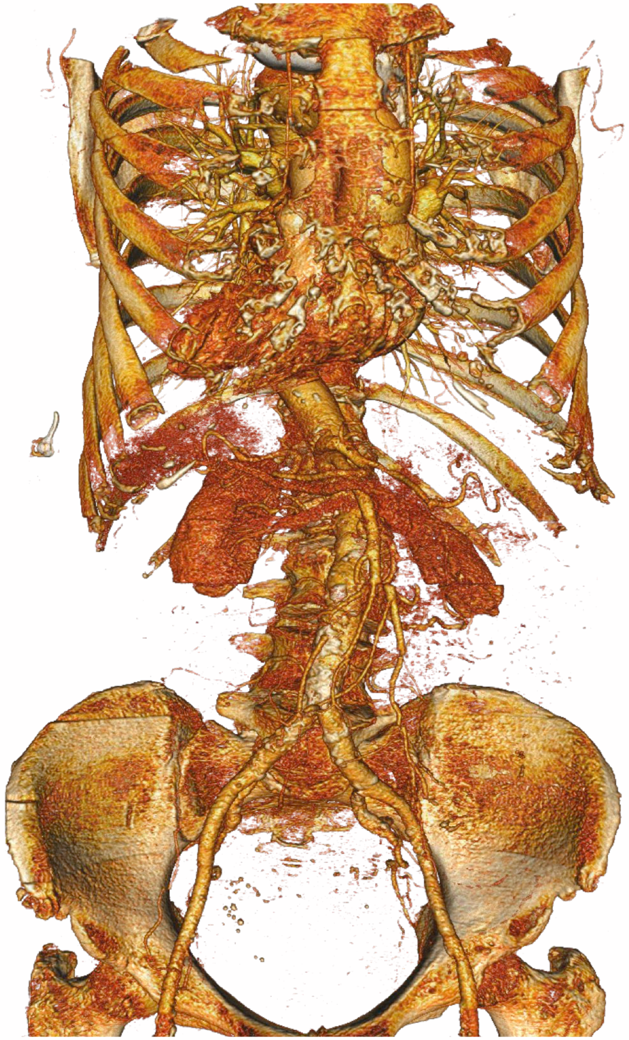


Session: 3D-01 -- 3D Image and Video Analysis and Compression

Presented by: Omniah Nagoor

Introduction

- Data compression forms a central role in handling the bottleneck of data storage, transmission and processing.
- Data compression techniques can be divided into two main types: lossy and lossless compression.
- Choosing which type to use relies on the application requirements.
- For medical image compression, the lossless approach is more appropriate since it recovers the original data without any loss in quality.

Related Work

State-of-the-art **Classical** Methods: **(Lossless)**

- **Image Encoder:**

  JPEG2000 [1], JPEG-LS [2], CALIC [3], MRP [4].

- **Volumetric Encoder:**

  JP3D [5], HEVC [6], 3D-CALIC [7], M-CALIC [8], 3D-MRP [9].

Related Work

State-of-the-art **Deep Learning** Methods: **(Lossy)**

- Dimensionality reduction (Autoencoders) [10].
- Super-resolution images or video reconstruction [11].
- Estimating pixel likelihood (Auto-regressive) [12].
- Generative compression [13].

Related Work

State-of-the-art **Deep Learning** Methods: **(Lossless)**

- The current deep learning literature for lossless compression usually combine a density estimator model with an arithmetic coder.
- The density estimator can be categorized into various types:
  - Fully connected NN [14].
  - Recurrent Neural Network (LSTM/GRU) (DeepZip) [15].
  - A recursive bits-back coding with hierarchical latent variables (Bit-Swap) [16].

Motivation

- According to Diagnostic Imaging Dataset Statistical Release published by NHS, between September 2018 to September 2019 over 45 million medical images acquired for clinical use including 5.8M CT scans and 3.7M MRI scans [17].

Motivation

- Especially for clinical purposes, artefacts that introduced by lossy compression could result in misleading diagnosis and unfavorable treatment.

Motivation

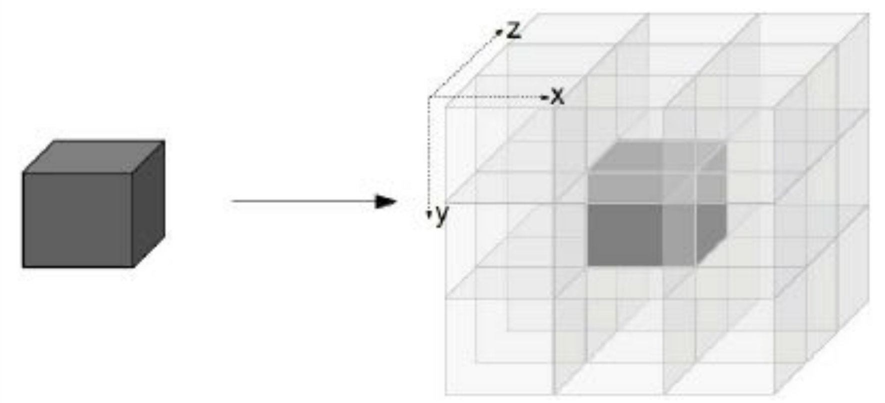
- There is a need for a compression tools that:
  - Utilizes deep learning technique for Lossless compression performance.
  - Has computationally efficient (parallelized) encoding/decoding performance.
  - Achieves a higher compression ratio compared to the state-of-the-art lossless compression methods.

Contributions

- A novel 3D predictor model using neural network that achieves lossless compression for volumetric medical images.
- A computationally efficient model that achieves higher compression ratio when compared to state-of-the-art lossless compression methods.
- Empirically, demonstrate the robustness and generalization of our proposed models on many datasets for higher dynamic range (16 bit-depths).

Proposed Method

- The regression problem can be solved by learning a mapping function f that predict the output $\hat{y}$ from an input sequence X through the back-propagation process given a training dataset.

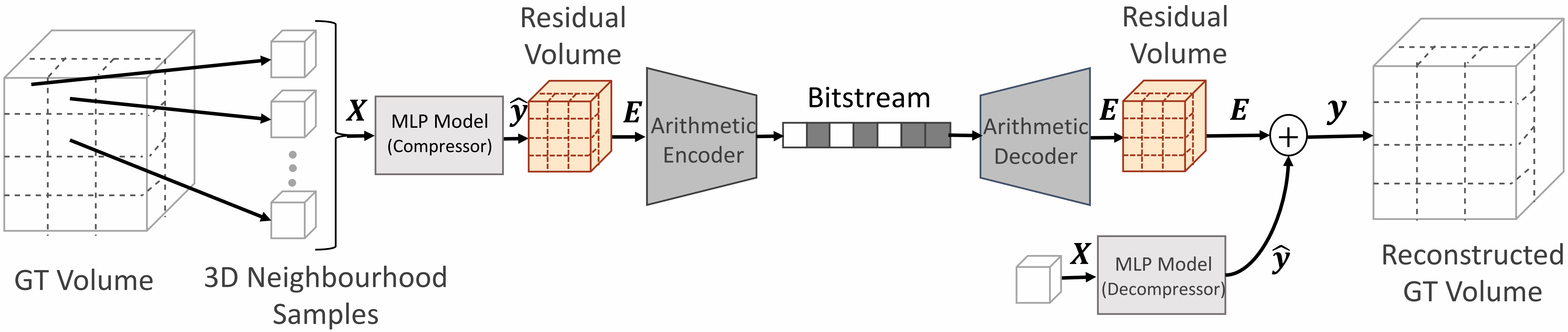


Proposed Method

- Given a data distribution defined over $X \in R^N$, where X contains input samples from the same distribution $X = \{x_1, x_2, \dots, x_n\}$ forms a 1D vector of immediately neighboring voxel-intensities.
- We learn a differentiable mapping function $\hat{y} = \mathrm{f}(X)$ that maps the input vector X to a predicted value $\hat{y}$ to minimize the differences with the ground truth voxel value y, where $\mathrm{f}(X)$ is represented using a neural network model.
- The residual (prediction) error E:

$$E = y - \hat{y}$$

Proposed Method



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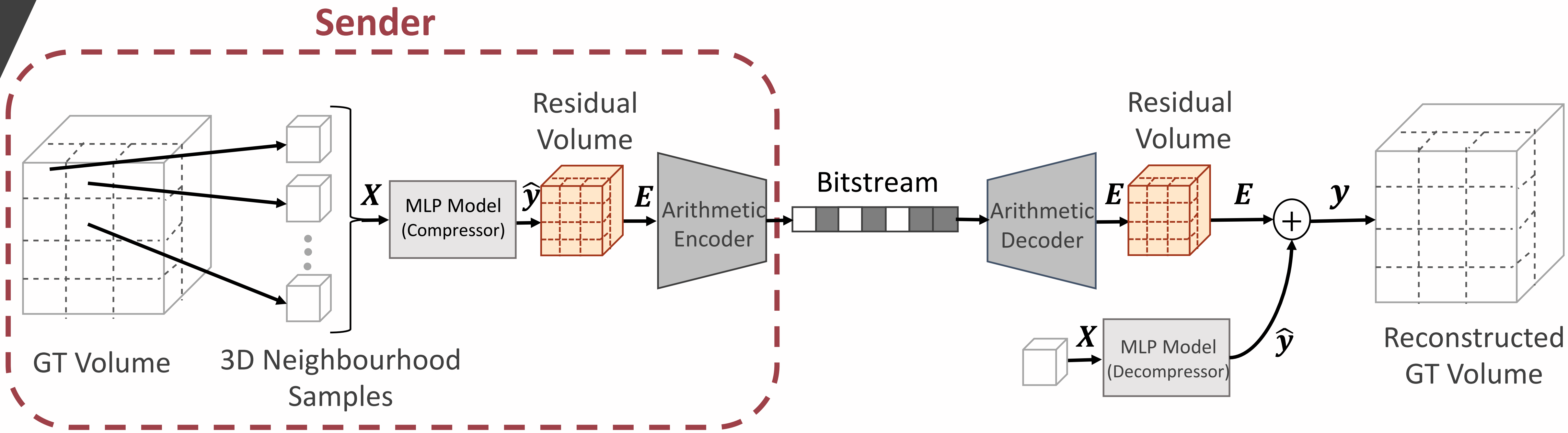

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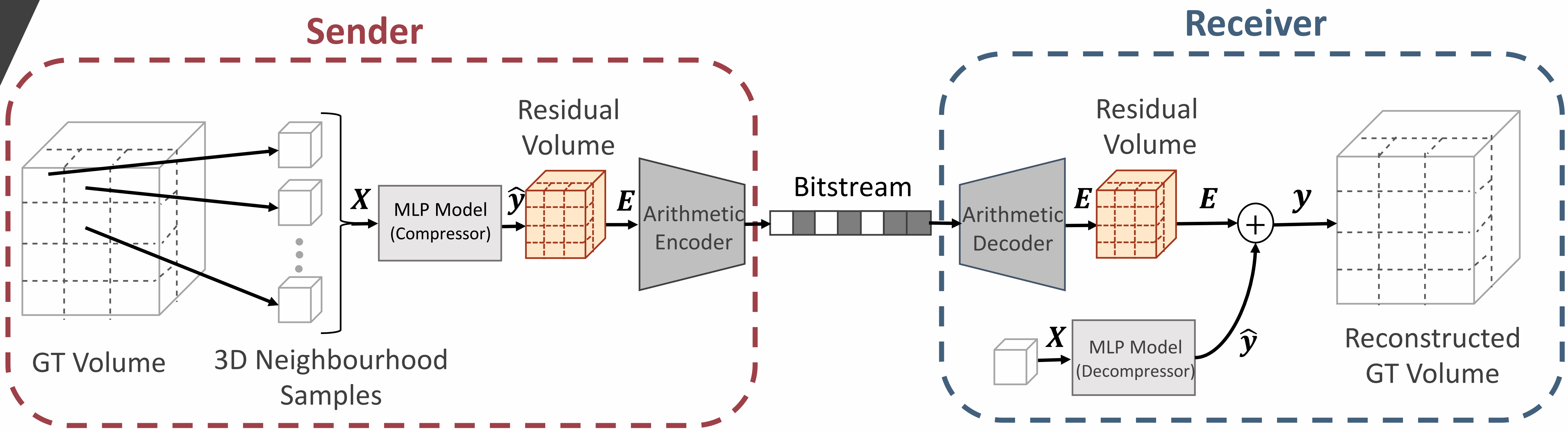

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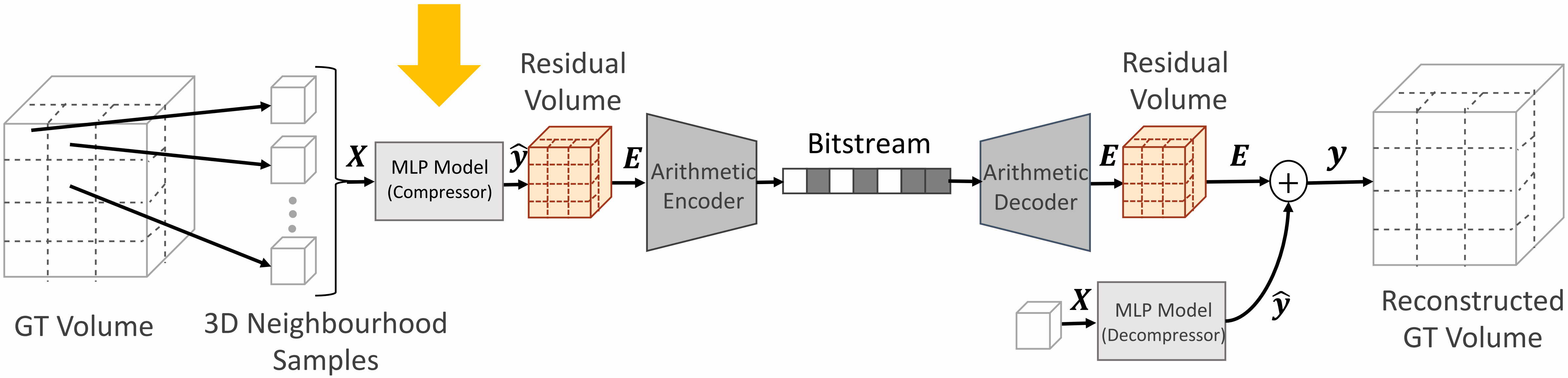

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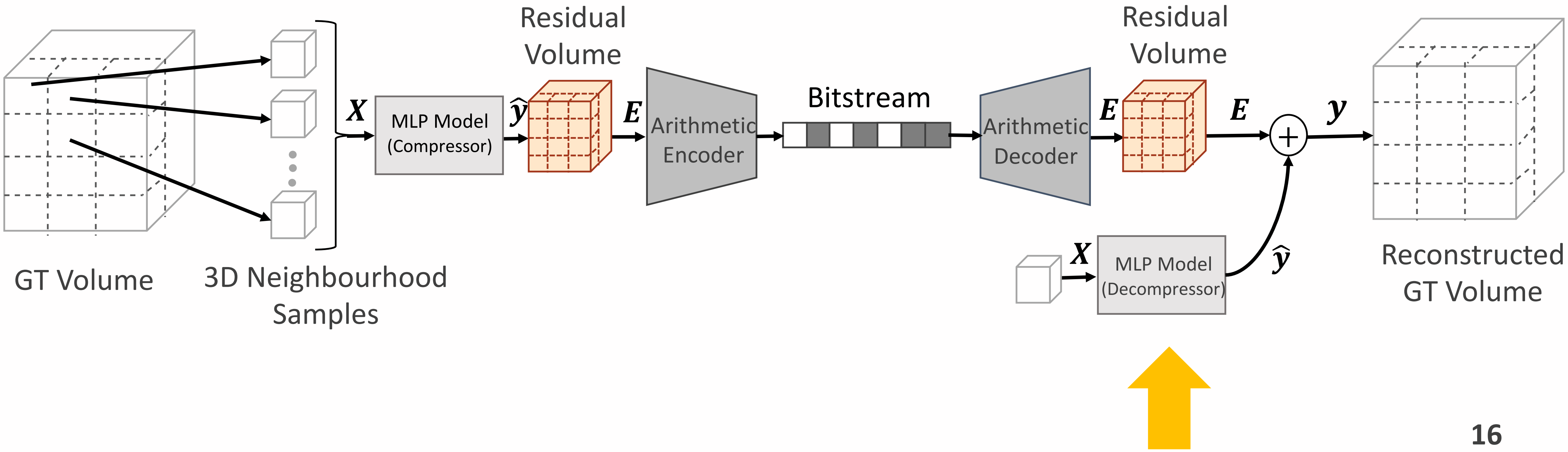

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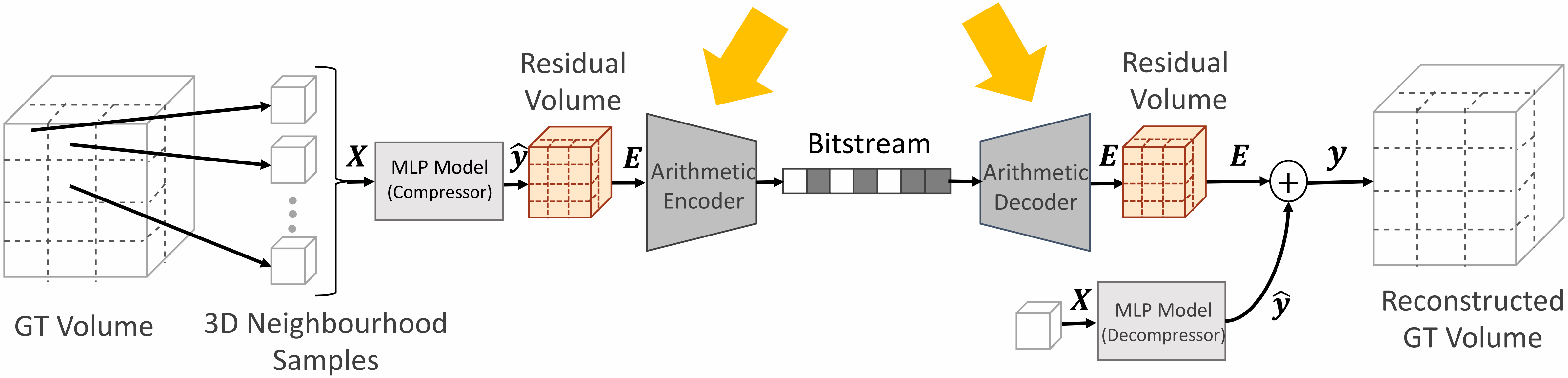

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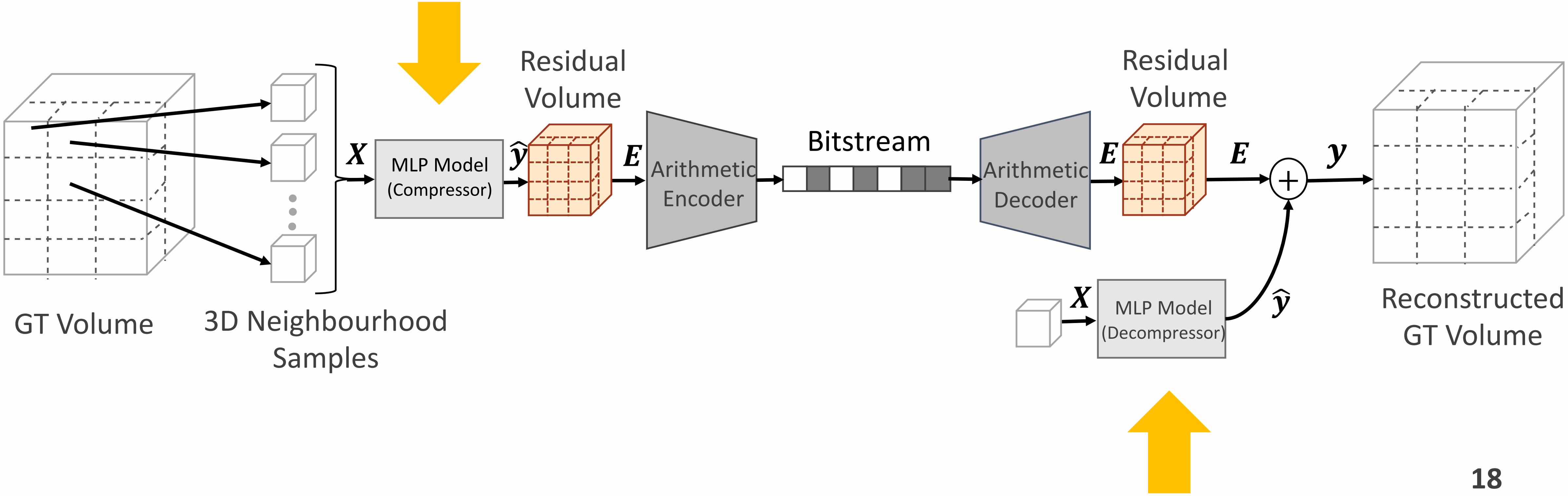
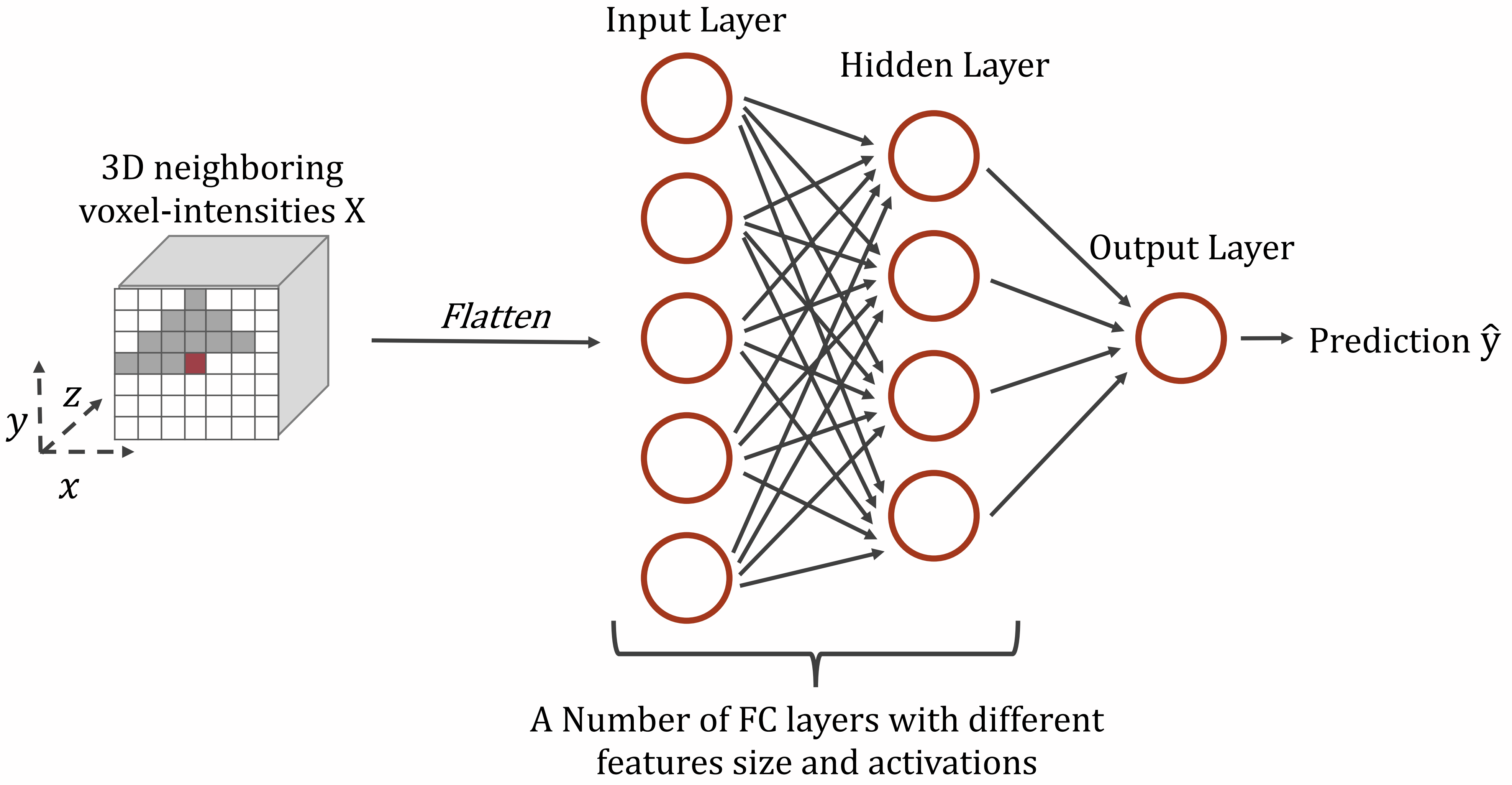


Network Architecture

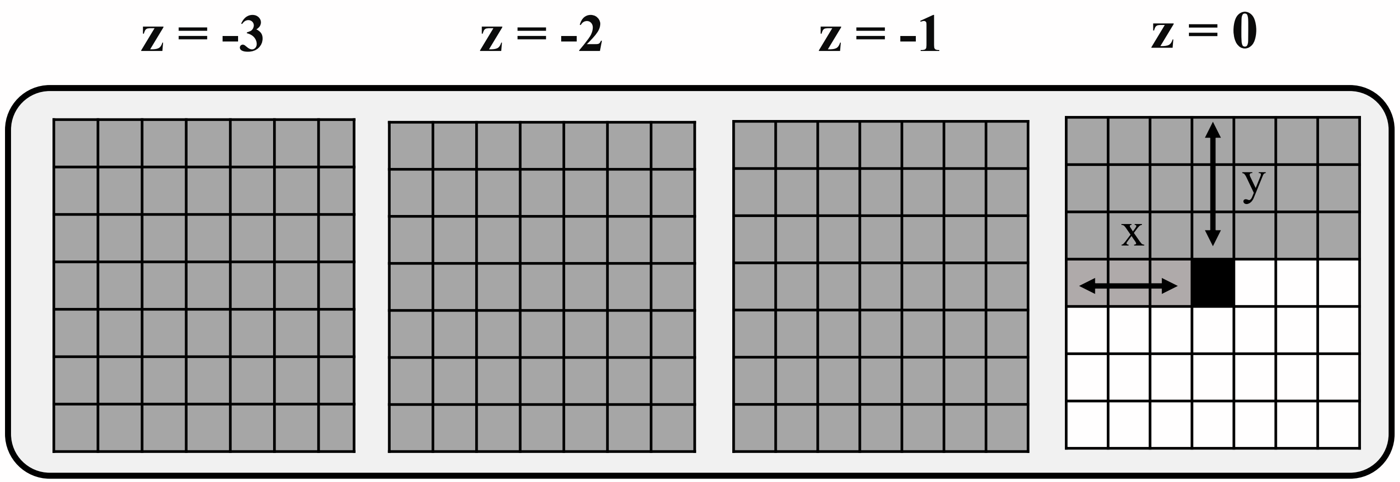


Network Architecture

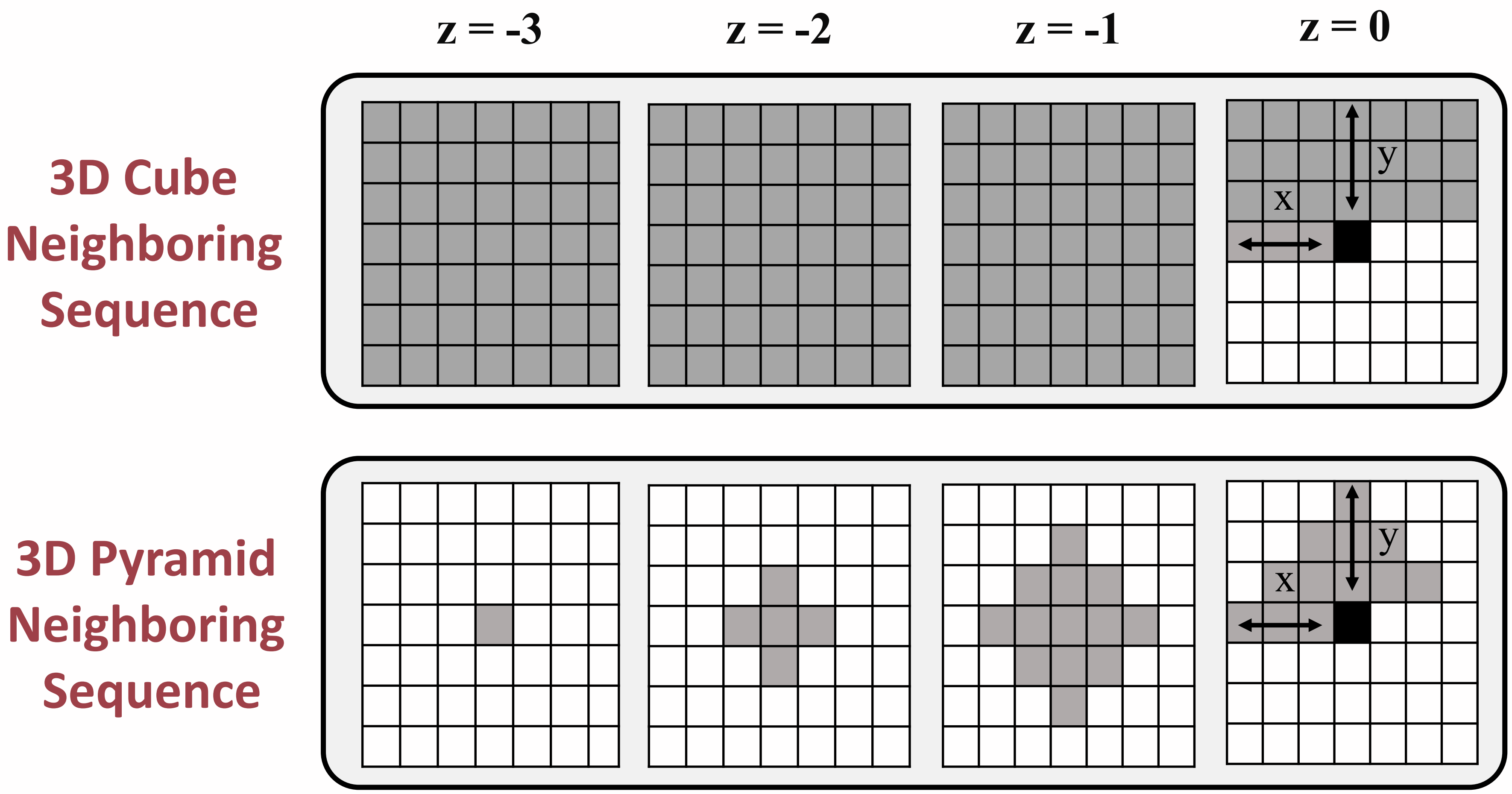
Layer	Number of Neurons	Activation Function Used
Fully Connected	1024	LeakyRelU
Fully Connected	512	LeakyRelU
Fully Connected	256	LeakyRelU
Fully Connected	128	LeakyRelU
Output	1	Linear

Local Sampling

3D Cube Neighboring Sequence



Local Sampling



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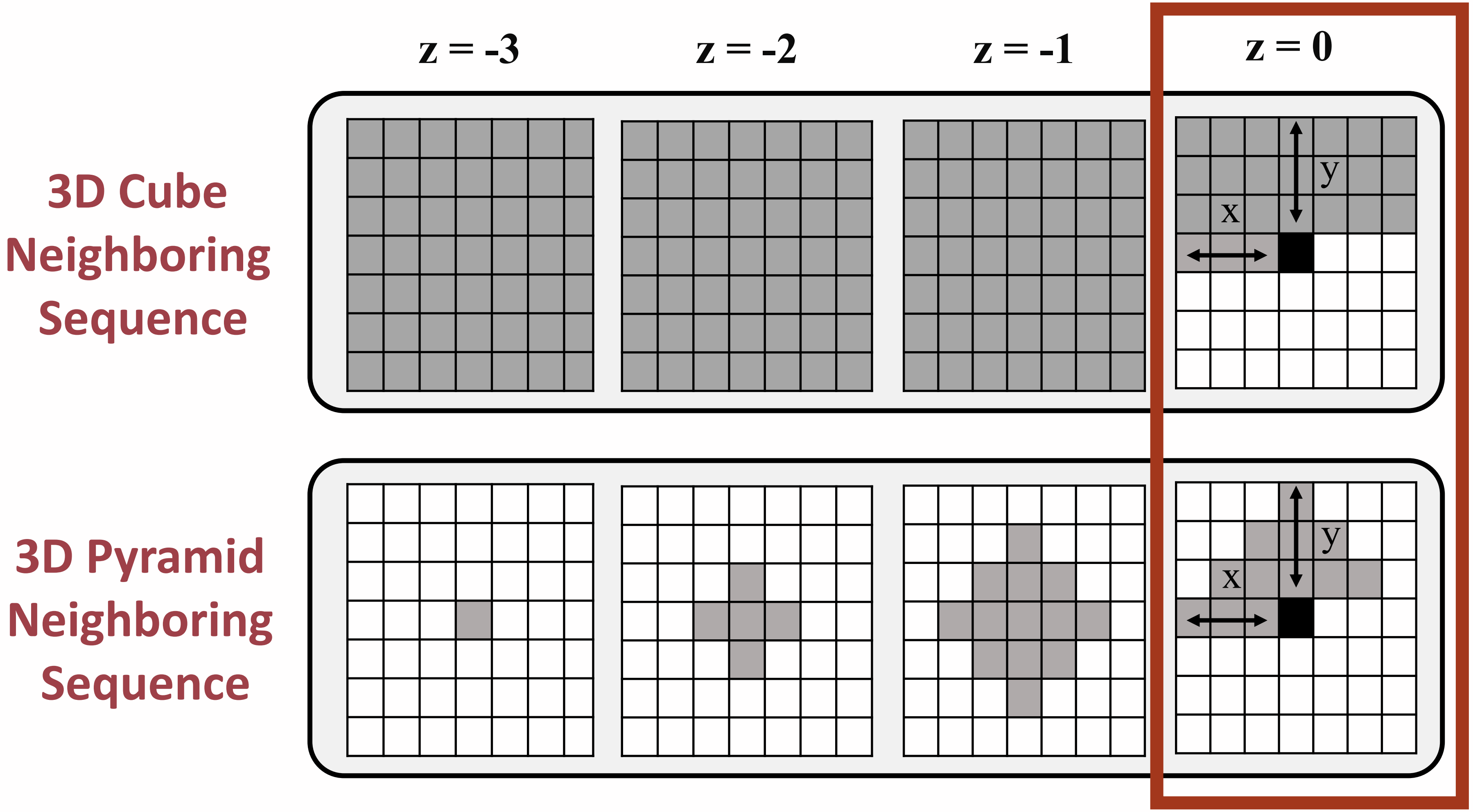


Local Sampling

- All volume values are normalized to the range [-1,1] and the volume is padded, as determined by the block size, by its minimum voxel value.
- Padding the volume is crucial in order to include the edge and corner cases in training.
- All the 3D sequences will be flattened to 1D vectors and randomly shuffled before inputting them to the predictor models.

Hyper Parameters

Model ID	Sampling Space	Shapes of the input Neighboring Block	Hyper Parameters
1	All samples were generated from 10 slices extracted from one volume (patient 40)	3D Cube input sequence (11x11x11)	Batch size = 256, learning rate = 2e-4, no L2 regularization, no dropout, and no batch normalization
2	All samples were generated from 10 slices extracted from one volume (patient 40)	3D pyramid input sequence (13x13, 9x9, 5x5, 1x1)	Batch size = 32, learning rate =3e-5, no L2 regularization, no dropout, and no batch normalization

Loss Function

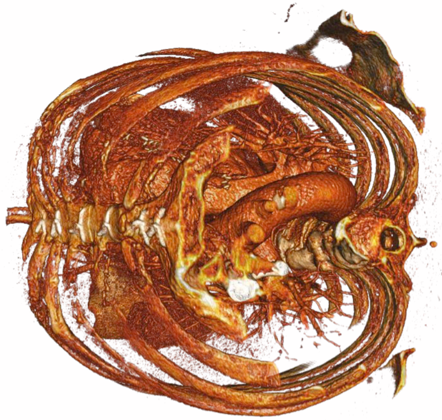
$$L_{Joint} = MAE + \lambda(1 - |PCC|)$$

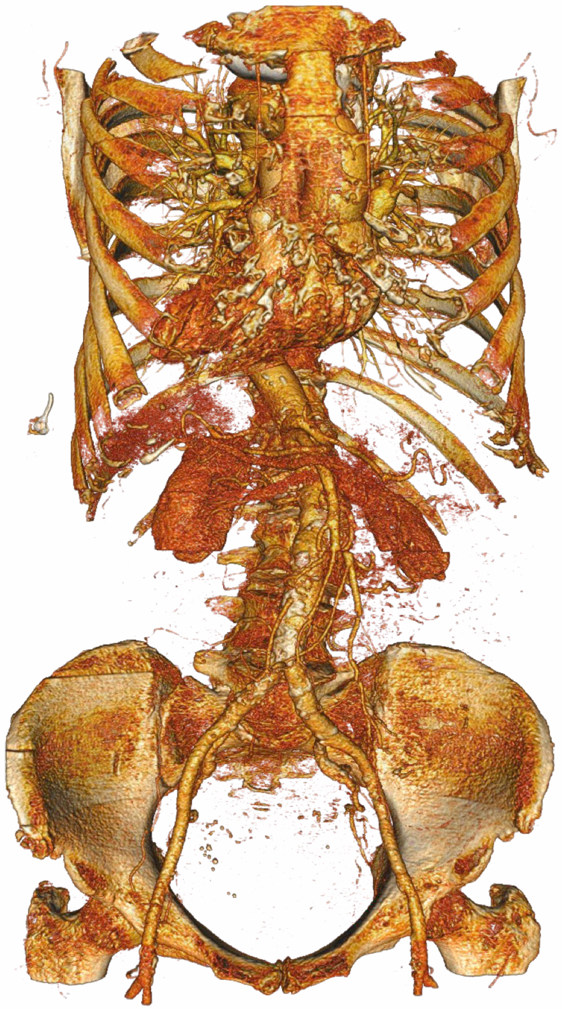
$$MAE = \frac{\sum_{i=1}^{n} |y - \hat{y}|}{n}$$

$$PCC = \frac{cov(y, \hat{y})}{\sigma_y \sigma_{\hat{y}}}$$

Result & Discussion

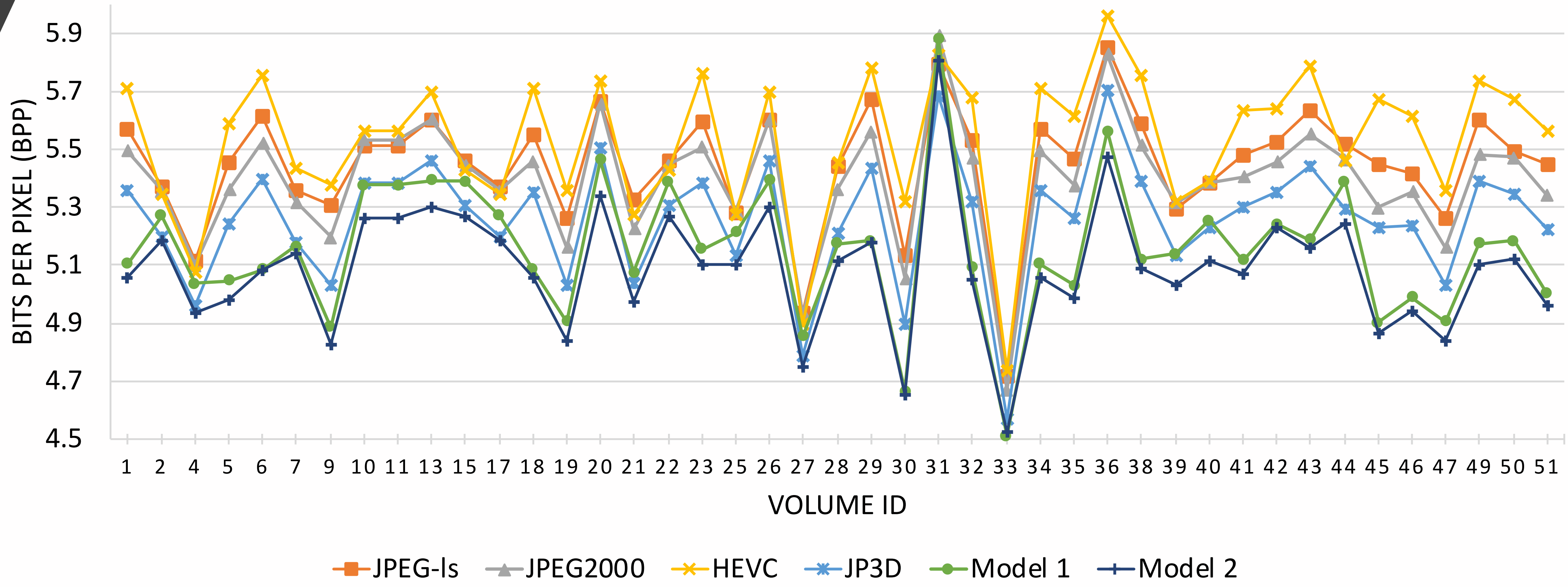
- We evaluated the compression performance in bits-per-pixel (bpp) of the proposed neural network models in comparison to the state-of-the-art lossless compression methods including JPEG-LS, JPEG2000, JP3D and HEVC.
- Our models were trained on one training set. However, the evaluation was conducted on two different test sets:
  - Testset1 (42 volumes)
  - Testset2 (2 volumes)





Result & Discussion (Testset1)

Comparing the compression ratio in BPP for the proposed models with the state-of-the-art lossless compression methods over 16-bits volumes on Testset1



Result & Discussion (Testset2)

Set Type	Volume ID	Pixel Spacing, Slice Thickness	JPEG-ls	JPEG2000	HEVC	JP3D	Model 1	Model 2
Training Set	40	0.625, 0.625, 0.625	5.387	5.387	5.389	5.23	5.256	**5.119**
Testset2 [18], [19]	CT Lung R004	0.830, 0.830, 5.00	5.937	6.014	**5.739**	5.967	6.664	6.715
	CT Lung R013	0.623, 0.623, 5.00	5.747	**5.539**	5.835	5.623	5.959	5.847

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	CT Lung R013	0.623, 0.623, 5.00	5.747	**5.539**	5.835	5.623	5.959	5.847
Resampled Testset2	CT Lung R004	0.625, 0.625, 0.625	5.459	5.243	-	5.195	4.915	**4.904**
	CT Lung R013	0.623, 0.623, 0.625	5.698	5.485	-	5.375	**5.237**	**5.238**

Conclusion

- We proposed a novel lossless compression system using a neural network for volumetric medical images (16 bit).
- Two localized sampling methods were introduced and evaluated on real 3D volumetric medical imaging datasets.
- The comparison study shows that our method outperforms the standard lossless compression methods.
- It also suggests that the proposed method is feasible to generalize to unseen dataset while retains satisfactory performance.

Future Work

- Study of generalization across samples with different pixel spacing or scan quality.
- The effect of model size and weight sparsity on compression ratio from transmitting both the compressed representation and decoder.
- Optimization of the decoder to leverage parallelism over the diagonal leading edge to reduce decode time.

References

[1] David, T., & Marcellin, M. (2012). JPEG2000 Image Compression Fundamentals, Standards and Practice: Image Compression Fundamentals, Standards and Practice. Vol. 642.

[2] Weinberger, M. J., Seroussi, G., & Sapiro, G. (2000). The LOCO-I lossless image compression algorithm: Principles and standardization into JPEG-LS. *IEEE Transactions on Image processing*, *9*(8), 1309-1324.

[3] Wu, X., & Memon, N. (1996, May). CALIC-a context based adaptive lossless image codec. In *1996 IEEE International Conference on Acoustics, Speech, and Signal Processing Conference Proceedings* (Vol. 4, pp. 1890-1893). IEEE.

[4] Matsuda, I., Mori, H., & Itoh, S. (2000, September). Lossless coding of still images using minimum-rate predictors. In *Proceedings 2000 International Conference on Image Processing (Cat. No. 00CH37101)* (Vol. 1, pp. 132-135). IEEE.

[5] Schelkens, P., Munteanu, A., Tzannes, A., & Brislawn, C. (2006, May). JPEG2000. Part 10. Volumetric data encoding. In *2006 IEEE International Symposium on Circuits and Systems* (pp. 4-pp). IEEE.

[6] Flynn, D., Marpe, D., Naccari, M., Nguyen, T., Rosewarne, C., Sharman, K., ... & Xu, J. (2015). Overview of the range extensions for the HEVC standard: Tools, profiles, and performance. *IEEE Transactions on Circuits and Systems for Video Technology*, *26*(1), 4-19.

[7] Wu, X., & Memon, N. (2000). Context-based lossless interband compression-extending CALIC. IEEE Transactions on Image Processing, 9(6), 994-1001.

[8] Magli, E., Olmo, G., & Quacchio, E. (2004). Optimized onboard lossless and near-lossless compression of hyperspectral data using CALIC. IEEE Geoscience and remote sensing letters, 1(1), 21-25.

[9] Lucas, L. F., Rodrigues, N. M., da Silva Cruz, L. A., & de Faria, S. M. (2017). Lossless compression of medical images using 3-d predictors. *IEEE transactions on medical imaging*, *36*(11), 2250-2260.

References

[10] Theis, L., Shi, W., Cunningham, A., & Huszár, F. (2017). Lossy image compression with compressive autoencoders. *arXiv preprint arXiv:1703.00395*.

[11] Lai, W. S., Huang, J. B., Ahuja, N., & Yang, M. H. (2017). Deep laplacian pyramid networks for fast and accurate super-resolution. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 624-632).

[12] Toderici, G., Vincent, D., Johnston, N., Jin Hwang, S., Minnen, D., Shor, J., & Covell, M. (2017). Full resolution image compression with recurrent neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 5306-5314).

[13] Santurkar, S., Budden, D., & Shavit, N. (2018, June). Generative compression. In *2018 Picture Coding Symposium (PCS)* (pp. 258-262). IEEE.

[14] Ayoobkhan, M. U. A., Chikkannan, E., & Ramakrishnan, K. (2018). Feed-forward neural network-based predictive image coding for medical image compression. *Arabian Journal for Science and Engineering*, *43*(8), 4239-4247.

[15] M. Goyal, K. Tatwawadi, S. Chandak and I. Ochoa. (2019). DeepZip: Lossless Data Compression Using Recurrent Neural Networks. In *2019 Data Compression Conference (DCC).* (pp. 575-575). doi: 10.1109/DCC.2019.00087.

[16] Kingma, F. H., Abbeel, P., & Ho, J. (2019). Bit-swap: Recursive bits-back coding for lossless compression with hierarchical latent variables. In ICML.

[17] S. Dixon. (2018, Sep). Diagnostic imaging dataset statistical release. In NHS England, UK. Tech. Rep.

[18] B. Zhao, L. H Schwartz, and M. G Kris. (2015). Data fromrider lung ct. the cancer imaging archive. TCIA.

[19] Zhao, B., James, L. P., Moskowitz, C. S., Guo, P., Ginsberg, M. S., Lefkowitz, R. A., ... & Schwartz, L. H. (2009). Evaluating variability in tumor measurements from same-day repeat CT scans of patients with non–small cell lung cancer. *Radiology*, *252*(1), 263-272.

Thank You