




1 DICaught: A Python Package for 3D Medical 2 Imaging Augmentation

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7 Summary

8 DICaught is a Python package based on the popular image augmentation library Albu-
9 mentations ([Buslaev et al., 2020](#)), with specific enhancements for working with volumetric
10 medical images, such as Computed Tomography (CT) scans. This package provides a collec-
11 tion of over 40 powerful augmentation techniques that can be seamlessly integrated into a
12 machine-learning pipeline to augment volumetric medical images. The package was designed
13 to incorporate the image acquisition metadata available in DICOM headers, allowing users to
14 create transformations that are consistent with those acquisition parameters for specific CT
15 systems and reconstruction kernels. DICaught extends the success of the Albu-
16 mentations library for two-dimensional (2D) image augmentation to the realm of three-dimensional (3D)
17 images, offering a comprehensive set of transformations and augmentations, ranging from
18 pixel-level intensity transformations to spatial transformations, all designed and optimized for
19 3D data.

20 Statement of need

21 The recent advancements in machine learning have significantly improved the performance of
22 deep learning models across various domains and applications. However, the success of these
23 models still largely rely on a significant amount of labeled and annotated training data. This
24 is a particular limitation in medical imaging applications where imaging data annotation and
25 the establishment of a reliable reference standard is expensive, time-consuming, and typically
26 requires clinician expertise. DICaught supports the efficient use of available labeled and
27 annotated data by providing augmentations that are consistent with preexisting imaging data
28 annotations available in the form of masks, bounding boxes, and keypoints.

29 Considering the distinct geometric and operational factors inherent to 3D images, several
30 toolkits have been developed to perform transformations in the 3D space domain; SimpleITK
31 ([Yaniv et al., 2017](#)) provides a collection of spatial transformations, including linear and
32 deformable geometric transformations, as well as intensity-based transformations such as linear,
33 non-linear, and histogram-based intensity adjustments. In addition to supporting various
34 medical imaging tasks, augmentation methods in packages such as TorchIO ([Pérez-García et
35 al., 2021](#)) and MONAI ([Cardoso et al., 2022](#)) were designed to seamlessly integrate into popular
36 deep learning frameworks such as PyTorch, providing a convenient interface for integration
37 within deep learning pipelines. Packages such as Volumentations were uniquely developed
38 for the purpose of augmenting 3D volumetric images, offering specialized transformations for
39 enriching 3D imaging datasets during the training of deep neural networks.

40 DICaught offers a variety of transformations including geometric and intensity transforma-
41 tions, spatial distortions, and physics-based augmentations designed to enhance the diversity

of 3D image data. A subset of these transformations includes blurring techniques, such as median blur and Gaussian blur, that must utilize local spatial operations such as convolution to achieve the desired output. Notably, DICAUGMENT offers a unique capability by allowing users to choose between a 2D by-slice operation or a full 3D operation when applying different blurring augmentations in a pipeline. This flexibility caters to a variety of use cases and ensures that the blurring effects can be consistent across an entire 3D volume.

Additionally, DICAUGMENT enables users to construct custom augmentation pipelines with control over each individual transformation. Mimicking the Albumentations (Buslaev et al., 2020) package, DICAUGMENT utilizes the concept of augmentation probabilities. This feature allows users to assign a probability of occurrence to each transformation within a pipeline, enabling selective and stochastic augmentation of a dataset. By specifying different probabilities for various transformations, users can create diverse and balanced augmented datasets that reflect real-world variability. This level of control ensures that specific augmentations, whether it be intensity adjustments or geometric transformations, are applied with user-defined frequencies, therefore tailoring the augmentation process to the characteristics and use case of the dataset.

Compared to other augmentation packages, DICAUGMENT offers a unique advantage through the addition of physics-based augmentations that leverage metadata from DICOM files in CT imaging. During the reconstruction process of CT images, different manufacturers employ different reconstruction kernels, leading to distinct noise textures in the resulting images often characterized by the Noise Power Spectrum (NPS) (Solomon et al., 2012). DICAUGMENT utilizes the NPS profiles from the specific reconstruction kernel to generate noisy images that are consistent with the imaging acquisition and reconstruction parameters (Tward & Siewerdsen, 2008) from the system and acquisition parameters used to acquire the original CT dataset. To illustrate, we computed the NPS obtained from the noise insertion transformations offered by DICAUGMENT and compared it against simple white Gaussian noise, which is a common noise insertion method for data augmentation (e.g., MONAI (Cardoso et al., 2022) and Volumentations (Solovyev et al., 2022)).

For this experiment, we utilized a water phantom (Phantom Testing: CT, n.d.) scanned by a Siemens Somatom Definition Flash CT scanner with an exposure of 240 mAs, 120 kVp, and reconstructed with a B30f reconstruction kernel at 0.48 mm in-plane pixel spacing. The 2D NPS was estimated using the method proposed by Solomon et al. (Solomon et al., 2012); from the water phantom, we extracted a uniform volumetric region of $128 \times 128 \times 70$ dimensions and computed the 2D NPS of each slice by using:

$$NPS(u, v) = \frac{d_x d_y}{N_x N_y} \cdot |F[I(x, y) - P(x, y)]|^2 \quad (1)$$

In Equation 1, u and v represent spatial frequency (mm^{-1}) in the x and y directions, respectively, d_x and d_y are pixel size in millimeter space, N_x and N_y are the number of pixels in the x and y directions within the selected ROI (i.e. 128×128 px), F denotes the 2D Fourier transform, $I(x, y)$ is the pixel density of the uniform region in Hounsfield Unit at position (x, y) and P is the second order polynomial fit of I . Each estimated 2D NPS within the volumetric ROI is normalized by its integral across all frequencies and converted into a one-dimensional radial representation, $r = \sqrt{u^2 + v^2}$. The final normalized NPS (nNPS) was obtained by averaging the radial NPS curves across 70 slices within the volumetric image.

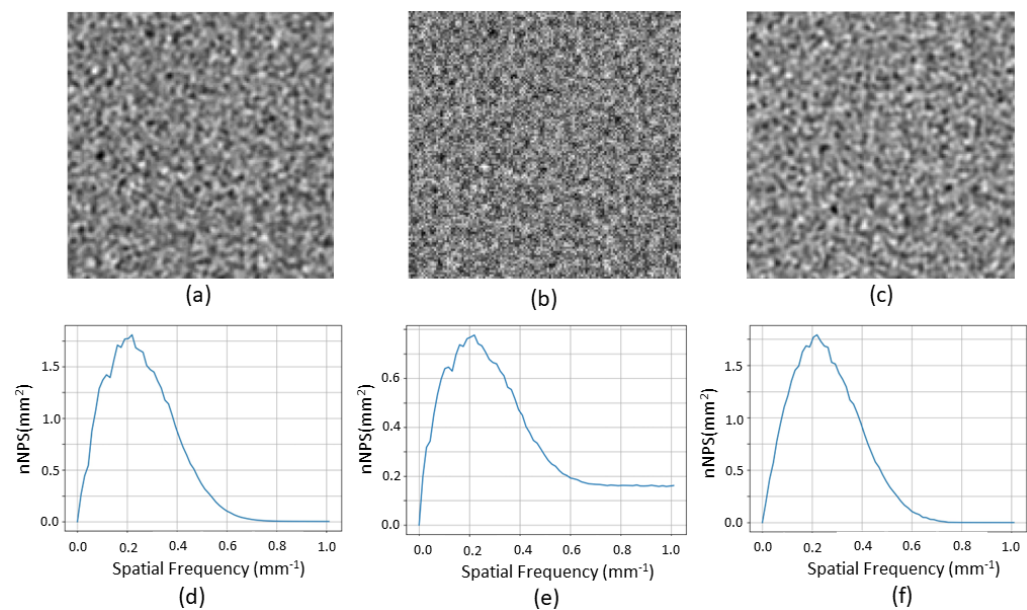


Figure 1: (a) Water phantom scanned by a Siemens Somatom Definition Flash CT scanner with imaging parameters set at 240 mAs, 120 kVP, and reconstructed with a B30f reconstruction kernel at 0.48 mm in-plane pixel spacing. The noise magnitude is computed as 9.46 Hounsfield units (HU). (b) Increasing the noise magnitude by adding white Gaussian noise, resulting in a noisy image with a magnitude of 16.01 HU. (c) Increasing the noise magnitude using DICAUGMENT, resulting in a noisy image with a magnitude of 16.08 HU. Figures (d), (e), and (f) illustrate the benefits of DICAUGMENT in offering augmentations consistent with the imaging parameters, demonstrated in terms of the Noise Power Spectrum (NPS) of the augmented image (i.e., inserting Gaussian noise produces a high-frequency tail in the NPS that is inconsistent with that of the Siemens scanner while our noise insertion method yields a shape in the NPS that is consistent with that of the Siemens scanner).

Figure 1(a) illustrates a slice of the noise region extracted from the uniform water phantom along with the corresponding estimation of the normalized Noise Power Spectrum (nNPS). Figure 1(b) illustrates the outcome of noise insertion using white Gaussian noise, a common approach for noise insertion (Cardoso et al., 2022), demonstrating the lack of correlation between adjacent pixels. Figure 1(c) shows the outcome of noise insertion by DICAUGMENT. Despite the increased magnitude of the noise, the correlation among adjacent pixels remained essentially unchanged, as evident in the normalized Noise Power Spectrum (nNPS) shown in Figure 1(f). This shows that a decreased CT exposure can be simulated through our augmentation process for specific CT imaging systems and kernels.

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