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Deep Analysis of Medical Image Augmentation Using Pixel-level Transformation Techniques

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Abstract

The exponential elevation of data-oriented technologies and deep learning models in recent years had a major impact on several fields, with image data being one of the primary areas of interest. Using a variety of imaging techniques and procedures, medical imaging produces images of the human body to diagnose and treat patients. Medical applications such as MRI, CT, ultrasound, X-ray, and PET imaging are used in the medical field. The shortage of medical image data is an important challenge owing to privacy issues, regulatory constraints, high cost, and the necessity for specialist annotations. In medical imaging, the growth and integrity of deep learning (DL) algorithms are hindered by low-quality images, limited access to diverse datasets, and a lack of longitudinal data. Augmentation techniques improve training data by introducing modifications not found in the original dataset. This bigger dataset reduces overfitting, enhances model generalization, and increases accuracy and dependability in practical applications. Within the scope of augmentation, the following techniques, such as geometric transformation, neural style transfer, adversarial training, data augmentation by GANs, and pixel-level transformation, are the most notable techniques. In medical imaging, the enhancement of the model's robustness may be attributed to pixel-level transformations, which include brightness modification, alteration of contrast, noise introduction, blurring, grayscale conversion, histogram equalization, gamma correction, and saturation. The model's generalization and robustness are improved by this method. By producing a variety of training samples, pixel-level transformations improve performance on unseen data. This paper provides an overview of pixel-level transformation-based image augmentation techniques.

Keywords: Deep Learning, Image Data Augmentation, Medical Image Processing, Over Fitting, Pixel-Level Transformation.

Introduction

Medical imaging techniques are used in medical studies, therapeutic interventions, and diagnostic imaging (1). Medical imaging allows for the generation of images of the inner structure of anatomy without the use of invasive methods (2). Medical images are used by healthcare professional's four functions including: diagnosis, treatment planning, monitoring, and research. Medical imaging contains the applications of various imaging methods, including image classification, to medical images such as X-rays, CT, MRI, ethnographies, and ultrasound images (3). Medical image recognition is increasing due to advances in image processing techniques, including analysis and enhancement (4). Data augmentation refers to methods for iteratively improving or developing model algorithms using unobserved data or hidden variables. It is especially important to overcome data sampling limitations in image datasets. Image data augmentation techniques help create medical images for diagnostics in a cost-effective manner, and achieve maximum test accuracy without the presence of large medical datasets. Image augmentation is a useful procedure for growing an image set for neural network types that do not involve images in addition. Image simulation and image synthesis have been studied and gaining popularity in the medical imaging community for some time (4). Medical Image processing devices are used to speed up and improve analysis of medical images. Medical imaging has undergone significant changes in the modern medical field. It is noteworthy that this technology can be used before surgery (5). Medical images are used by healthcare professional's four functions including: diagnosis, treatment planning, monitoring, and research (6). Medical imaging contains the

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applications of various imaging methods, including image classification, to medical images such as X-rays, CT, MRI, ethnographies, and ultrasound images (7). Various medical imaging procedures have been implemented over time and these methods vary depending on the procedure. Processing of medical images is a field of study that involves the development and application of methods and techniques for classifying and decoding medical images. DL models can be helped to do better by artificially generating diverse models with symmetrical classes in the training data set. The DL model works well and accurately when the data set is large enough in terms of size and quality (8).

The utilization of data sets in the analysis of medical images, such as for detecting and classifying abnormalities or diseases, is used to train machine learning algorithms (9). It addresses two problems for researchers: reducing over fitting and generating more data from a given amount of data. In addition, comprehensive testing of different data augmentation methods, such as histogram equalization, random translation, and cropping, shows that target finding accuracy can be improved, but the minimal effect (10).

Both the nature of the data set and the structure of the sample are important factors in selecting data augmentation. Various types of tests are performed to determine the model structure and the appropriate data augmentation for a particular data set (11). Data augmentation provides a solution by providing the model with different views of an image, which makes the model more general and allows it to extricate additional data from the original data set. The second problem is related to labelling; meaning that each sample in the original data set has a label augmenting the model preserves the original model size and assigns it to the augmented model (12). Generating new training cases through formal data augmentation involves transforming already existing data while maintaining the consistency and accuracy of the original labels. Models help to identify and innovate patterns, features, and structures in different situations (13). Data augmentation is a broad-range regularization technique for the purpose of enhancing the efficiency of a model. In other terms, the training data meets both the necessity of sufficient variety and size, and it can be accomplished through data augmentation. Pixel-Level transformation is the one of the techniques of data augmentation; it will modify the individual pixel values of an image without change image spatial structure. The input image is the only thing that is altered by pixel-level transforms; masks, bounding boxes, and key points remain unaltered.

Pixel-level transformation (or) transformations, are image sharpening, Image blurring, Histogram equalization, Noise addition, and Color manipulation. Each of these servers a unique purpose in enhancing and diversifying dataset. Its approach aims to create new models by making pixel-wise changes to the entire content of the image. These methods are commonly based on the MixUp like image structure modes and its derivatives such as Sample Pairing, AdaMixUp, mWh, and SmoothMix.

Typically, they blend the contents of two or more samples of image together. This is attained by accomplishing pixel-wise blending, typically by weighting and averaging the intensities of chosen images to generate synthetic images. These techniques can apply different photometric changes to the content of pixel. Pixel-level augmentation techniques are very useful for confronting adversarial attacks. Due to this characteristic, many works have proposed the use of pixel- and region-scale methods to improve both adversarial strength and accuracy of generalization. Noisy Mixup and Random Pixels are two techniques found to be more reliable types in pixel-level data augmentation techniques (14).

Convolutional neural network architecture was introduced in past study, which incorporates image data augmentation techniques to enhance biomedical image segmentation performance (14). The viewpoint issue was to be partially resolved by rotation and flipping; the lighting change was to be addressed by brightness, and the background and scaling problems were to be addressed by cropping and zooming. Most data augmentation strategies can generate numerous synthetic images based on existing samples, offering a quick and convenient solution (15).

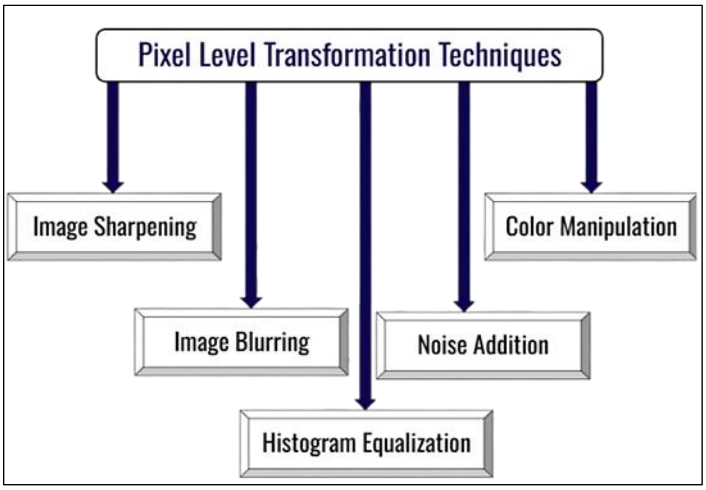


Figure 1: Types of Pixel-Level Transformation Techniques

Methodology

As shown in Figure 1, the four categories of image augmentation techniques that involve pixel level transformations include: sharpening, blurring, adding noise, equalizing histograms, and manipulating colour. Transformation methods may be applied at the pixel level to create additional examples of images through pixel intensity modification to provide models with greater diversity and greater robustness. Pixel-level image blending and domain-based data adaptation method perform better than the traditional method (16). Image sharpening has been introduced to enhance image contrast and brightness. Unsharp masking is used to sharpen the image and improve contrast. Add a contrast to the original intensity to make it easier to distinguish the foreground and background and enhance the edges of the image. Image sharpening methods are divided into two types: spatial domain and frequency domain methods (17).

Image blurring is an image processing function that allows applying a filter to the whole image (18). Different types of blur measurements are proposed to control and measure the effect of images. In 1997, one of the assessments was developed to improve image super-resolution methods and their blurring method was later used as a quality measure (18). The intensity of original image values is mapped to create an approximately equal distribution in the resulting histogram with histogram equalization. This suffers from the problem of not properly preserving local details as the image is manipulated globally (19). Over-enhancement of the image is a common result of equalization, leading to a visual data and intensity scale of loss (20).

Random variations in image intensity are called noise addition. In different methods noise can be added into an image. During the acquisition process, noise is produced in the transmission channel or sensor while an image is being created. This is used to make DL models more robust to various types of noise and to increase the training data set commonly required in applications of medical. Specific augmentation techniques, such as rotating, flipping, and adding various types of noise to data samples, can be manually scaled. Previous studies have revealed that color-based transformations are more effective than geometric transformation (21). Color jittering is a method that either uses random color manipulation or set color adjustment.

Medical Image Augmentation using Pixel -Level Transformation

Pixel-level transformations in medical image augmentation are used to maximize the robustness and variety of training data sets for machine learning models. Pixel-level transformation includes the following techniques for data augmentation: image sharpening, blurring, histogram equalization, noise addition, and color manipulation. This method is verified on a dataset of medical images and at the same time has less data context (22).

A digital image is an image represented digitally in a group of pixels, or more specifically, a combination of pixels. Each pixel in an image and device documents a group of numbers that summarize some of the attributes of this pixel, the intense color of the light, and its brightness (23).

These transformations preserve the underlying patterns and properties of the data while making minor changes. One significant way to augment data is to incorporate noise into both input and output data. Noise models are a very important part of image processing. It is an unnecessary signal used to destroy the original image quality. The image was distorted by some noises such as gaussian noise, salt and pepper noise, quantization, speckle noise, rayleigh noise, poisson noise, brown noise, and very basic noise.

The various Pixel-level transformation techniques applied on the following medical image modalities like MRI, CT and X-ray images are explained in the following section. Color manipulation can be applied to image augmentation such that it purposefully manipulates the color and, therefore, transforms its color characteristics to generate more variations for machine learning models to generalize. Because the models are learning from a wider spectrum of situations with the use of several lightings and different color intentions, they are rendered more resistant to real-world variations.

Dataset

The datasets used in this research cover a variety of medical imaging modalities and are openly accessible on Kaggle. The Alzheimer's Disease dataset has 1,279 MRI images. There are 5,863 JPEG-format X-ray images in the Chest x-ray Images (Pneumonia) dataset, the Knee x-ray Osteoporosis dataset includes knee radiographs and clinical variables for easy osteoporosis screening.

Image Sharpening

Image Sharpening is a pixel-level transformation that increases the contrast between pixel at an image's edges more pronounced. Image sharpening is an important imaging enhancement technique used in every field that requires understanding and analyzing images. Sharpness is the primary factor affecting image quality. Sharpness should be adjusted to the optimal value to improve image quality. Sharpening is essential for processing most digital images and then emphasizing them with texture and detail (17).

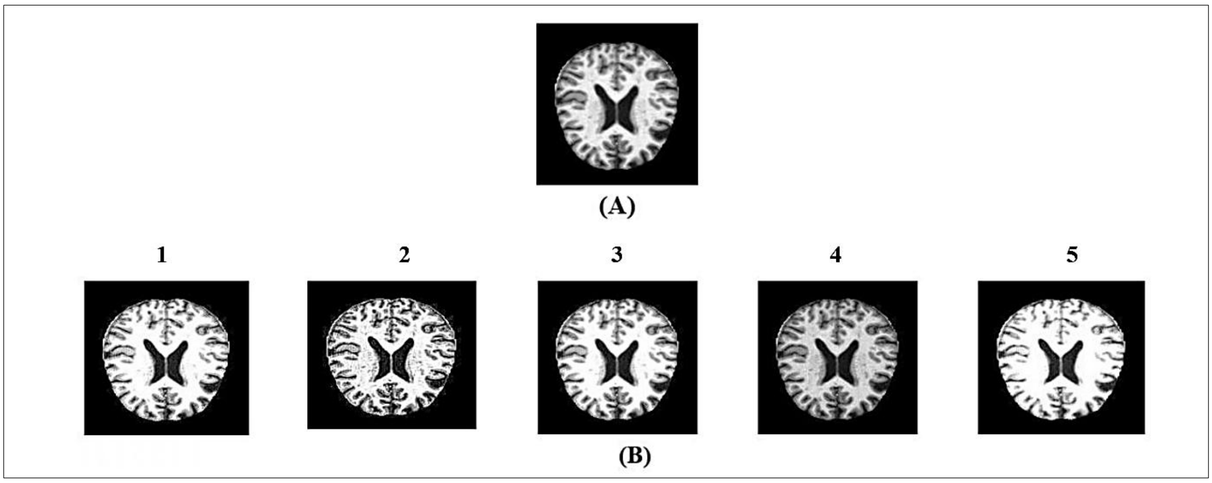


Figure 2: Image Augmentation Using Sharpening Techniques on MRI Slices: (A) Original Image and (B) Sharpened Augmented Images

Figure 2 depicts the application of sharpening techniques for data augmentation on an MRI slice image. The sharpening process uses five unique kernels; each designed with unique internal settings to enhance specific features and edges in the original image. These kernels range from light sharpening, subtle detail enhancement, strong sharpening to clearly emphasize edges, and extreme custom sharpening for high-end enhancement for precision to custom sharpness. These augmented images demonstrate how different types of sharpening can enhance image features, making them suitable for training medical analysis and DL models.

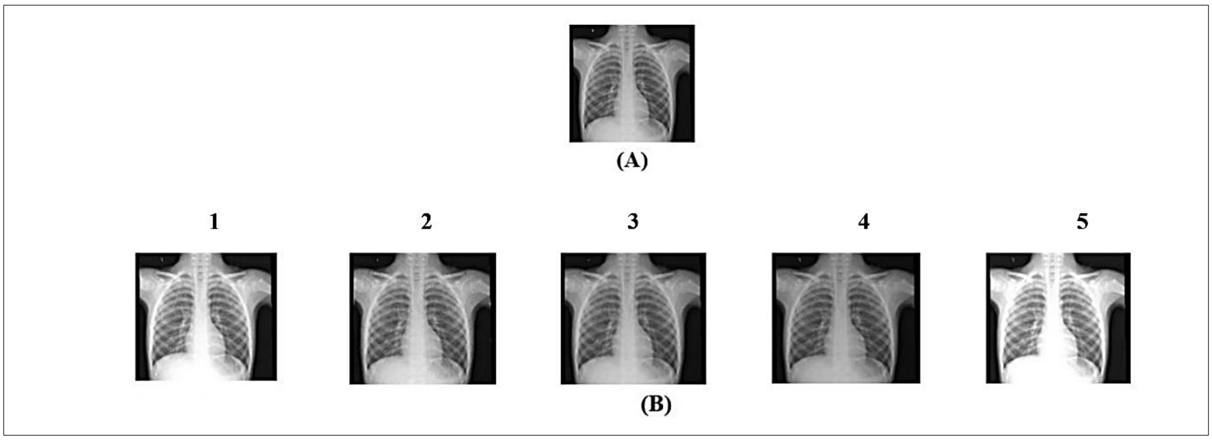


Figure 3: Image Augmentation using Sharpening Techniques on CT Images: (A) Original Image and (B) Sharped Augmented Images

Figure 3 illustrates the application of sharpening techniques for data augmentation, CT scan image. The sharpening process uses five types of kernels; each designed with unique internal structures to emphasize specific features and edges in the original image. Kernels range from mild sharpening, which uses reduced intensity corrections to maintain subtle enhancements, to strong sharpening, which introduces more pronounced edge emphasis. Other variations include a slight high-end enhancement and custom sharpening with reduced intensity for refined results. These augmented images demonstrate how various sharpening modification can enhance image features and its suitable for applications such as medical image analysis and DL model training.

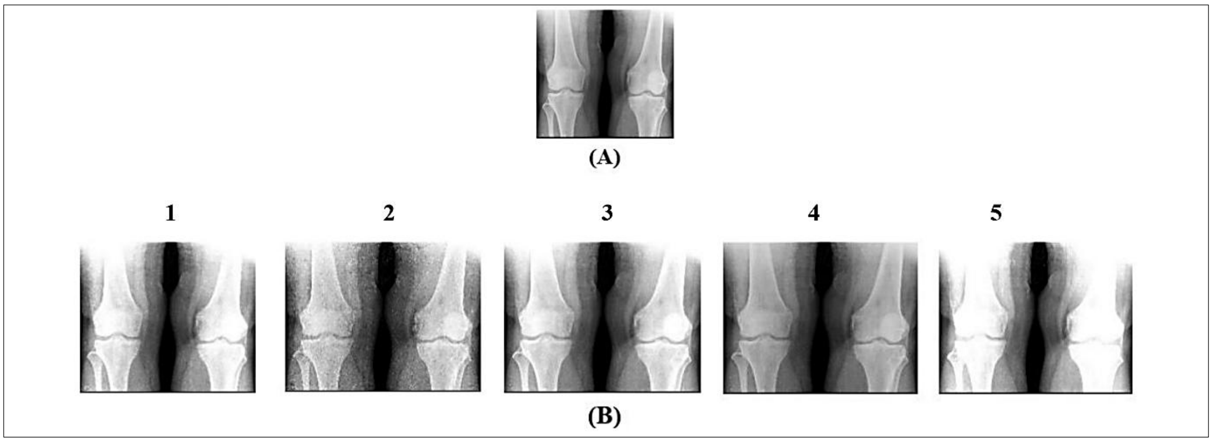


Figure 4: Image Augmentation using Sharpening Techniques on X-ray Images: (A) Original Image and (B) Sharped Augmented Images

Figure 4 illustrates sharpening techniques for data amplification in X-ray images. Five different kernels with different configurations improve the image's edges and features.

Image Blurring

Object or camera device movement during shooting, improper focus, noise, and other effects of the camera matrix can blur the image. Data augmentation is the method of supplementing data sets with similar data created from the information in a data set. This often involves applying bluring and other transformations to existing images (18).

Figure 5 showcases the effects of different blurring techniques applied to MRI slices. The first output image applies a Gaussian blur with a 5×5 kernel to the original image, effectively reducing G and smoothing details. The second output image scales the image by 1.5X before using the same Gaussian blur pixels to see the effect of resolution changes. The third image repeats the Gaussian blur without any changes for the baseline comparison. The fourth image uses a stronger Gaussian blur with a 5×15 kernel, which results in more pronounced smoothing. The final output image uses a median blur with a kernal size of 5, which effectively decrease noise while preserving edges. These techniques are used to analyze the impact of various types of blur and Kernal scales on image quality.

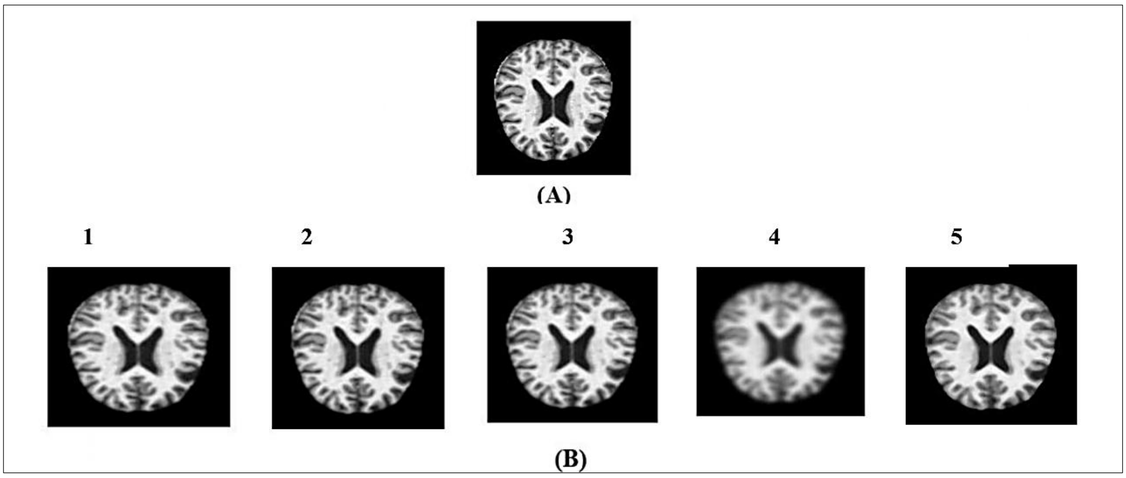


Figure 5: Image Augmentation using Blurring Techniques on MRI Slices: (A) Original Image and (B) Blurred Augmented Images

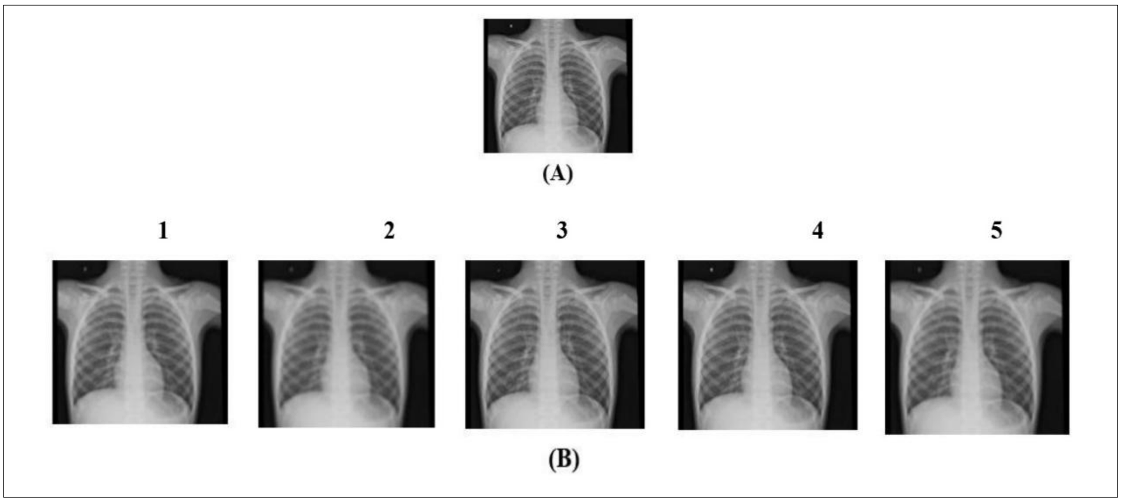


Figure 6: Image Augmentation using Blurring Techniques on CT images: (A) Original Image and (B) Blurred Augmented Images

Figure 6 illustrates the image augmentation of CT images using the blurring techniques. This image consists of two sections: Part (A) original image and (B) blurred augmented images. These blurring techniques include Gaussian and Medium blurs that introduce varying degrees of softness and noise reduction to images. Part (B) blurred augmented images shows a gradual loss of fine details, which is useful for training DL models to improve robustness against image distortions. This augmentation technique is essential in medical image analysis to enhance model generalization and performance in real-world scenarios.

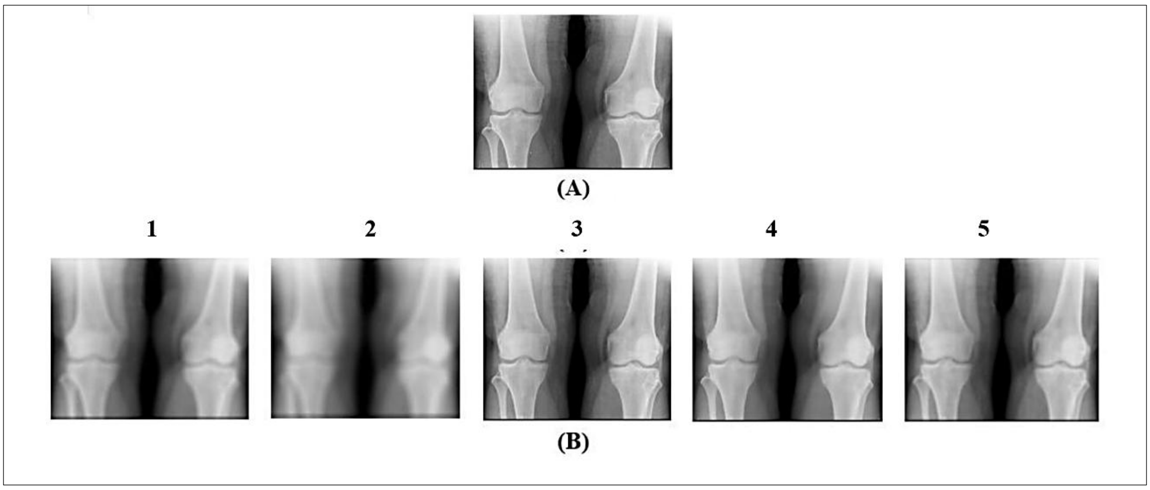


Figure 7: Image Augmentation using Blurring Techniques on X-ray images: (A) Original Image and (B) Blurred Augmented Images

Figure 7 illustrates the effects of various blurring techniques applied to an X-ray image. The (A) represents the original X-ray image. Blurred Image 1 and Blurred Image 3 show the application of Gaussian blur with a moderate kernel size, leading to noticeable smoothing of the image. Blurred Image 2 applies Gaussian blur after scaling the image, which results in a slightly different smoothing effect due to the increased image resolution. Blurred Image 4 uses a larger Gaussian kernel, resulting in a stronger blur that significantly reduces image details. Finally, Blurred Image 5 demonstrates the application of median blur, effectively reducing noise while preserving edge structures.

Histogram Equalization

One of the image techniques that increases contrast through histogram equalization is to modify the distribution of pixel values. It became a widely used technique for contrast development because this technique is simple and useful (24). The purpose of this method is to obtain a uniformly distributed histogram using the overall density function of the input image, and it attempts to modify the spatial histogram of an image to more closely match the uniform distribution (25). Basically, histogram equalization is used to improve contrast.

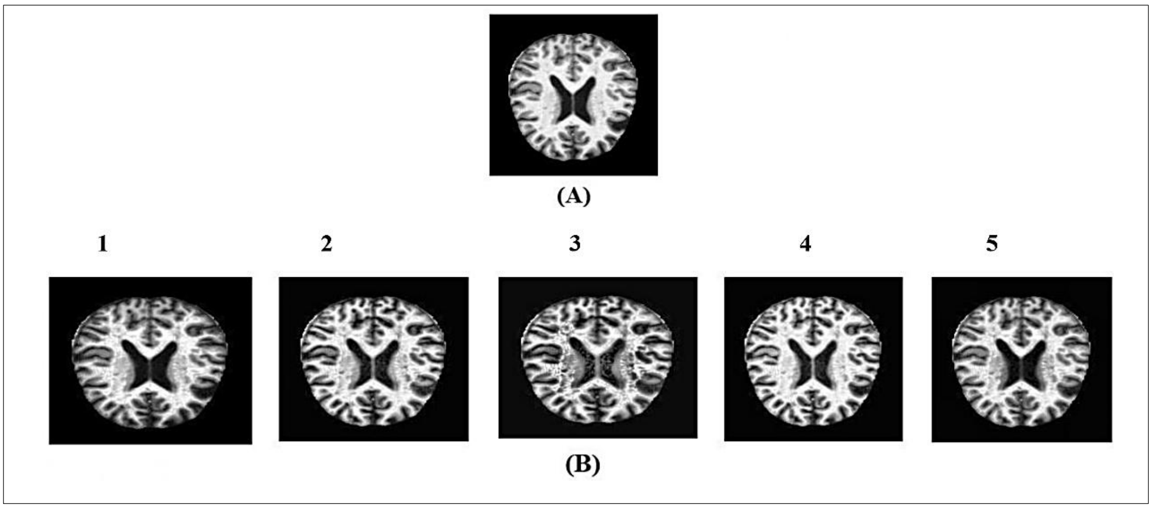


Figure 8: Image augmentation Using Histogram Equalization Techniques on MRI slices: (A) Original Image and (B) Histogram-Equalized Augmented Images

Figure 8 illustrates applied in Histogram Equalization Techniques applied in MRI Slices. The first output is created using basic histogram equalization, enhancing global contrast. The second uses CLAHE (Contrast Limited Adaptive Histogram Equalization) with a clipLimit of 3.0 and tileGridSize of [8, 8] for local contrast enhancement. The third applies CLAHE with a higher clipLimit of 10.0 for more aggressive contrast enhancement. The fourth uses a larger tileGridSize of [16, 16] for smoother adjustments, and the fifth employs a smaller tileGridSize of [4, 4] for finer local detail enhancement. These techniques improve the robustness of medical image analysis through diverse contrast adjustments.

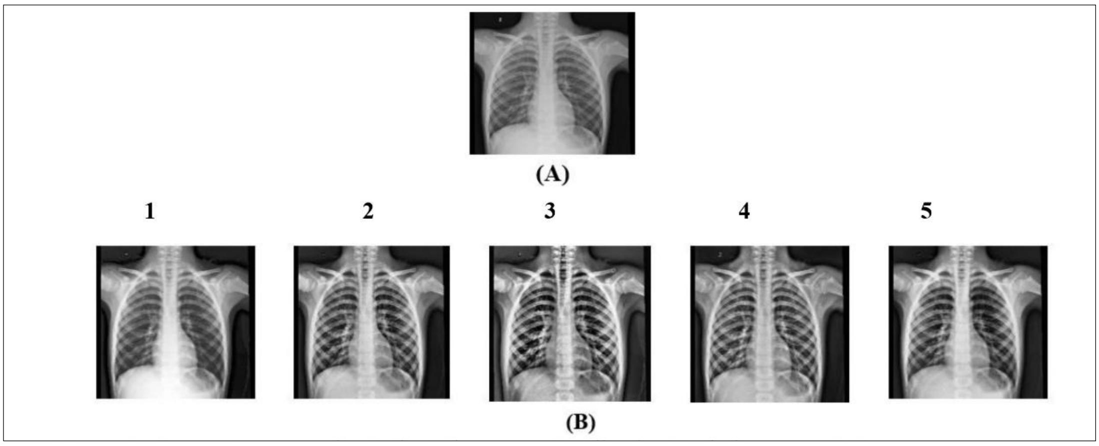


Figure 9: Image Augmentation Using Histogram Equalization Techniques on CT Images: (A) Original Image and (B) Histogram-Equalized Augmented Images

Figure 9 illustrates histogram equalization techniques applied to CT images. The first augmented image is created using basic histogram equalization, enhancing global contrast. The second uses CLAHE with a clipLimit of 3.0 and tileGridSize of [8, 8] for local contrast enhancement. The third applies CLAHE with a higher clipLimit of 10.0 for more aggressive contrast enhancement. The fourth uses a larger tileGridSize of [14, 14] for smoother adjustments, and the fifth employs a smaller tileGridSize of [5, 5] for finer local detail enhancement.

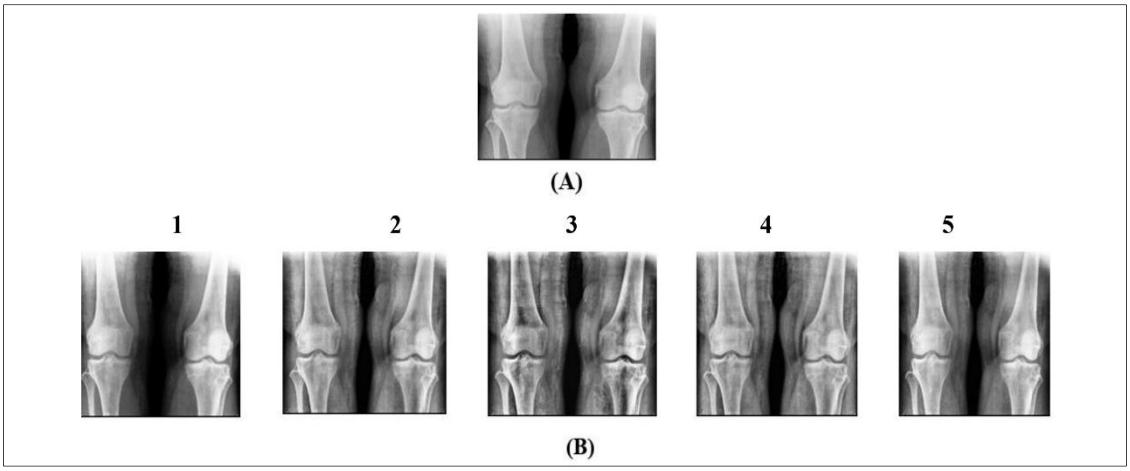


Figure 10: Image Augmentation using Histogram Equalization Techniques on X-ray Images: (A) Original Image and (B) Histogram-Equalized Augmented Images

Figure 10 shows image augmentation using histogram equalization techniques in X-ray images. The first augmented image is created using basic histogram equalization, enhancing global contrast. The second uses CLAHE with a clipLimit of 2.5 and tileGridSize of [8, 8] for local contrast enhancement. The third applies CLAHE with a higher clipLimit of 8.0 for more aggressive contrast enhancement. The fourth uses a larger tileGridSize of [14, 14] for smoother adjustments, and the fifth employs a smaller tileGridSize of [5, 5] for finer local detail enhancement.

Noise Addition

Noise is a variation in brightness that can ruin part of an image. The unwanted signal in noise degrades the image quality by changing the pixel value (26).

Noise is the deliberate manipulation of pixels to change their potential meaning. When compared to human comprehension, this type of imperfection can be especially annoying to machines. Noise level is a very important dimension in many image applications, such as image segmentation, super resolution, and other applications (27). Gaussian noise is the most common type of noise encountered in imaging. Salt and pepper noise during transmission can easily corrupt digital images, resulting in a significant decrease in their visual quality (28).

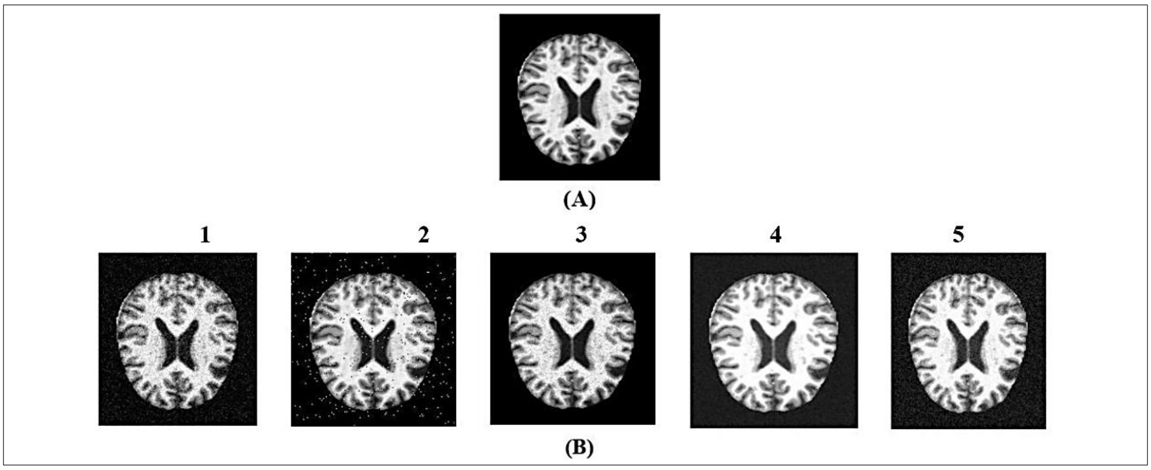


Figure 11: Image Augmentation Using Noise Addition on MRI Slices: (A) Original Image and (B) Noise Augmented Images

Figure 11 demonstrates the addition of various noise types to an MRI grayscale image to simulate real-world imperfections. Gaussian noise (σ=25) was introduced in Figure 1, leading to a grainy effect. Salt and pepper noise (P=0.02) was applied in Image 2, scattering white and black pixels randomly. Image 3 includes speckle noise, generated by adding pixel-dependent random values. Poisson noise with a rate parameter of 30 was incorporated in Image 4, causing random intensity variations. Finally, Image 5 features local noise, created by adding random uniform noise with a range of [0, 50]. These augmentations diversify the dataset, enhancing model robustness for noise-affected real-world applications.

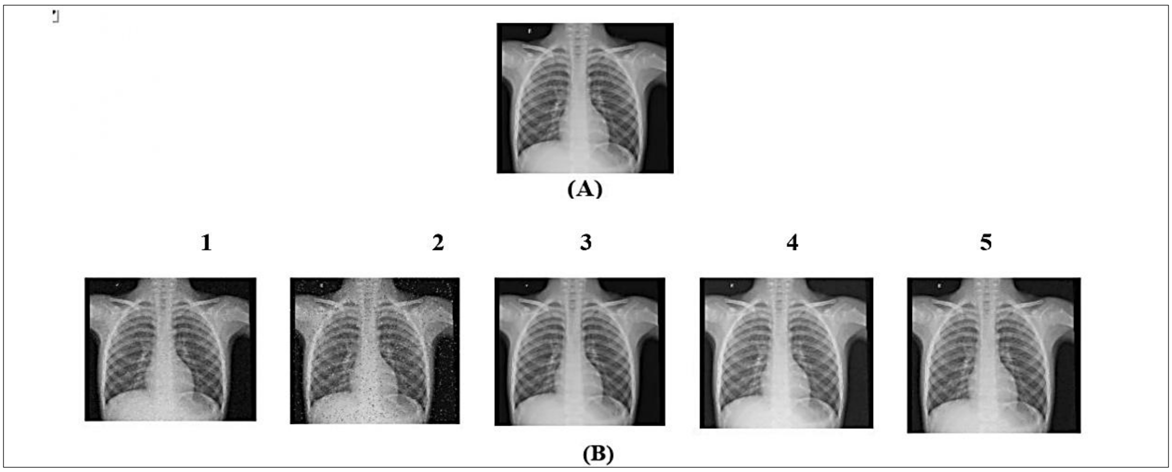


Figure 12: Image Augmentation Using Noise Addition on CT image: (A) Original Image and (B) Noise Augmented Images

Figure 12 showcases the application of five different noise types to a grayscale medical image with reduced noise intensities to maintain image quality. To generated image (B), a subtle grain effect was achieved by inserting Gaussian noise with a mean of 0 and reduced standard deviation (σ=15). Salt and pepper noise was introduced by introducing scattered white and black pixels, thus creating Image 2. Speckle noise, applied with a reduced standard deviation (σ=0.1), generated

Image 3, exhibiting fine variations. Poisson noise, implemented with a reduced rate parameter (λ=20), led to Image 4, which shows minimal intensity irregularities. Finally, local uniform noise, sampled from a narrower range ([0,20]), was applied to produce an Image 5 with soft intensity variations.

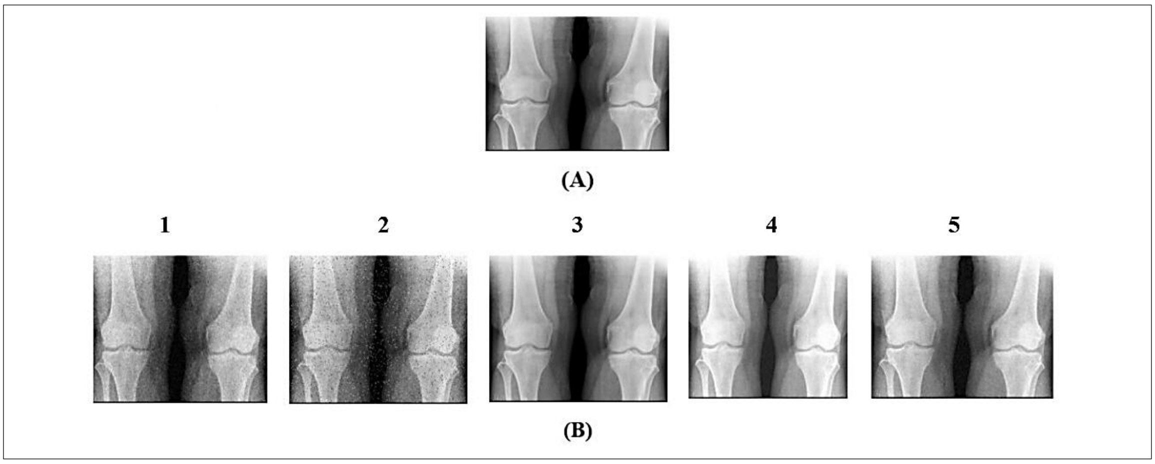


Figure 13: Image Augmentation Using Noise Addition on X-Ray Image: (A) Original Image and (B) Noise Augmented Images

Figure 13 illustrates the procedure of applying five various noise types to a grayscale x-ray image for augmentation. The image had a grainy appearance due to the addition of Gaussian noise, which had a mean of 0 and an increased standard deviation (SD) (29) (σ= 25). Next, salt and pepper noise were applied with an increased probability (P = 0.06), generating an image that contains randomly scattered white and black pixels. Speckle noise, characterized by multiplicative noise patterns, was added with an increased standard deviation (σ=0.2) to generate Image. Poisson noise, implemented with a higher rate parameter (λ=40), created Image, exhibiting irregular intensity variations. Finally, uniform local noise, sampled from a broader range ([0,40]), generated an image showing soft variations in pixel intensities. These images are valuable for training robust DL models by simulating real-world noise in medical imaging datasets.

Color Manipulation

In pixel-level transformation augmentation, color manipulation includes brightness, contrast, saturation, hue, and the color channels. These involve simulating different lighting, changing colors, or simulating different camera settings, which can help improve generalization of DL models by creating diverse conditions in images.

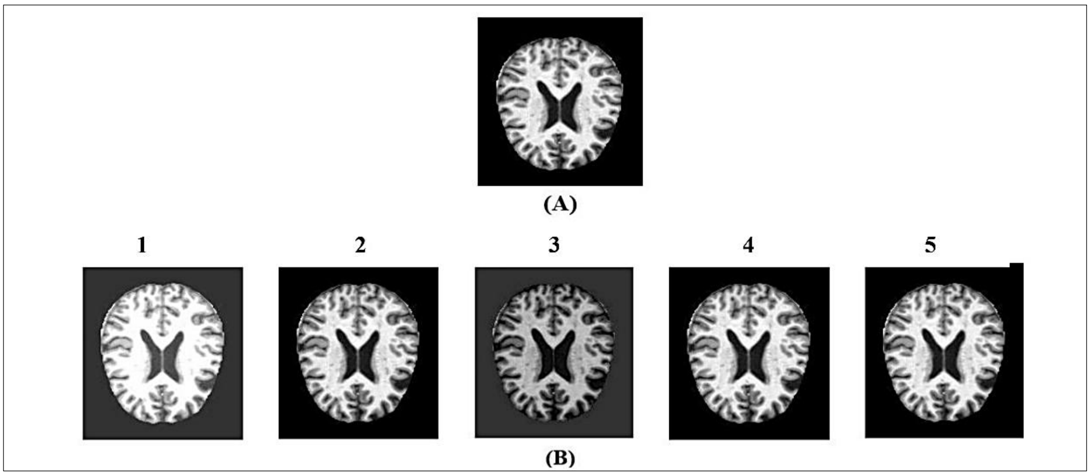


Figure 14: Image Augmentation Using Color Manipulation on MRI Slices: (A) Original Image and (B) Color-Manipulated Images

Figure 14 illustrates the outcomes of various color manipulation techniques applied to MRI images. The original is shown in the first image, unmodified MRI Slice. The first manipulated original image enhances brightness, improving the overall luminance. The second image reduces brightness, resulting in a darker appearance. The third manipulated image adjusts contrast, making light and dark areas more distinguishable. The fourth image shifts the hue by converting the image to HSV color space and altering the hue, introducing a color shift. Finally, the fifth image eliminates all color information by converting the MRI scan to grayscale and converting it to the RGB color space for consistency. These changes are very useful for MRI data sets, which helps to build robust DL models for clinical image prospect analysis.

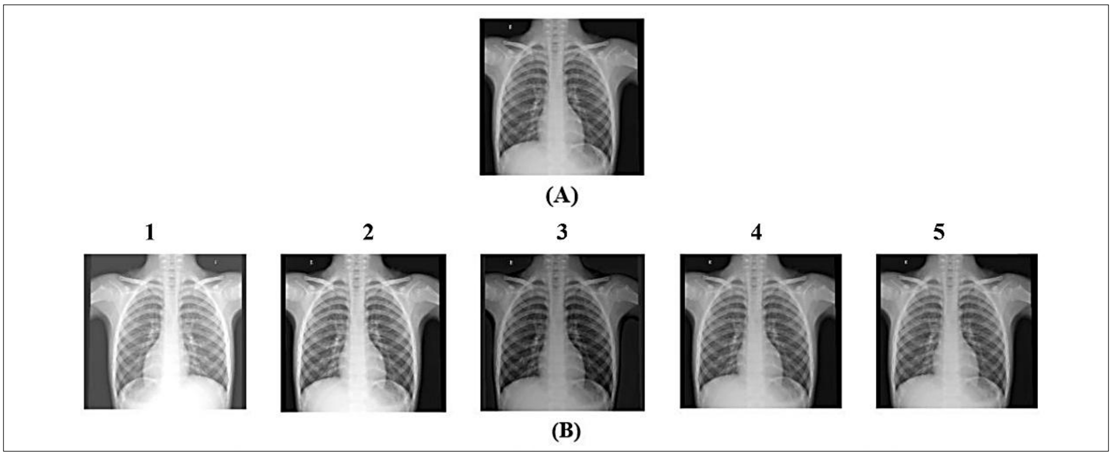


Figure 15: Image Augmentation Using Color Manipulation on CT image: (A) Original Image and (B) Color-Manipulated Images

Figure 15 shows images illustrating the effects of color manipulation techniques. The first image is the original unaltered CT image. The first manipulated image brightens by increasing the brightness by a fixed value. The second image darkens by decreasing the brightness by a fixed value. The third image corrects the contrast by measuring pixel intensities, emphasizing the differences between light and dark areas. The fourth manipulation changes the hue by converting to the HSV color space, changing the color values, and introducing a color shift. Finally, the fifth image is converted to grayscale, removing color information and returning to RGB for consistency. These changes are valuable for increasing the quality of medical image datasets or improving visual analysis.

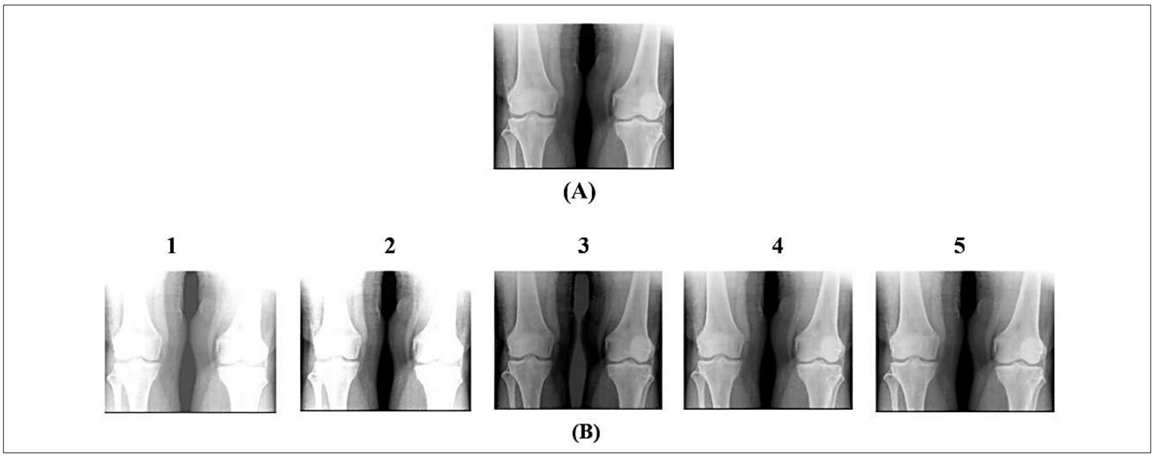


Figure 16: Image Augmentation Using Color Manipulation on X-Ray Images: (A) Original Image and (B) Color-Manipulated Images

Figure 16 shows images illustrating the effects of color manipulation techniques. The original image is the first image. The X-ray image is an unaltered image that serves as the base reference. The five subsequent images show the different types of color manipulation changes applied to the original image. These manipulated images show significant changes in brightness, variation, and intensity, each highlighting different visual features of x-rays. Such transformations are used to enhance specific features, improve visibility, or create augmented data sets for tasks such as medical image analysis or training machine learning models. This approach ensures better adaptability of the models to alternative in image conditions.

Results and Discussion

Along with Metrices used for the Evaluation of Image Augmentation Techniques

Evaluation metrics are significant for assessing the function and efficiency of DL models. Metrics provide a standard method for computing and evaluating models or techniques in areas such as image processing and machine learning. They provide a quantitative basis for comparing the performance of different models. These metrics are required for measuring the success of a model through indicators such as precision, accuracy, and recall. Test accuracy, weighted F1 score, multi-class sensitivity, and multi-class specificity are metrics used to evaluate a DL model.

The quality of an image can be assessed using the peak-to-noise ratio (PSNR) and the structural similarity index measurement (SSIM) (30). They provide numbers indicating the differences between an original image and the augmented images (31). Such quantification is essential for developers and researchers to evaluate the efficiency of various image augmentation algorithms. For these reasons mentioned above, we choose for both metrics, such as SSIM and PSNR, for evaluating the image augmentation techniques (32). The PSNR is a measure of the relationship between the maximum potential force, the force represented by the original frame (Equation [1]), and the effect of noise distortion on the accuracy of that representation given by the compressed frame (33).

$$\text{PSNR} = 10.log_{10} \frac{MAX_I^2}{MSE} \qquad [1]$$

where,

MAX - The maximum possible pixel value of the image.

MSE - The mean square error between the input and augmented image.

SSIM is a measure that assesses the structural similarity between two images (33). Three factors are used to measure how similar images are: brightness, contrast, and structure (34). SSIM is a full-reference image quality rating index with a range [0, 1] (35). The value will be larger when the image distortion is less (Equation [2]) (36).

$$\text{SSIM}(_{a,b}) = (2\mu_a \mu_b + M_1)(2\sigma_{ab} + M_2) / (\mu_a^2 + \mu_b^2 + M_1)(\sigma_a^2 + \sigma_b^2 + M_2) \qquad [2]$$

where,

σ_a^2 and σ_b^2 - variances of the images a and b.

σab - difference between images a and b.

These metrics offer different perspectives on image quality: PSNR focuses on pixel-level errors, while SSIM provides a more holistic view of structural similarities.

Table 1: SSIM and PSNR Results of Pixel-Level Transformation Augmentation

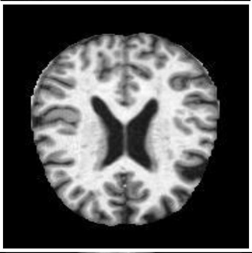
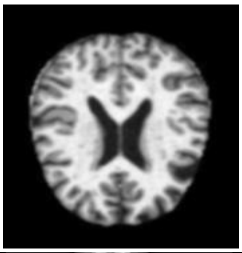
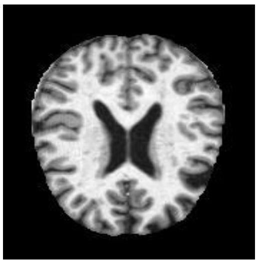
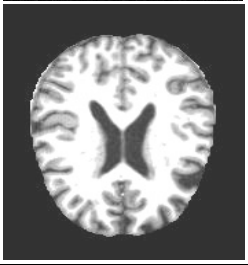
Method	Original Image	Augmented Image	PSNR Value	SSIM Value
Sharpening			15.99 dB	0.6252
Blurring			29.55 dB	0.9498
Histogram Equalization			22.90 dB	0.8779
Noise Addition			20.44 dB	0.1621
Color Manipulation			14.66 dB	0.4691

Table 1 displays the values of SSIM and PSNR with sample figures after applying pixel-level transformation augmentation. The SSIM and PSNR are critical metrics of evaluation that are utilized to assess image quality when tested to pixel-level transformation methodologies. When applied to pixel-level transformations, such as color manipulation, noise addition, histogram equalization, image sharpening, and blurring, these metrics aid in measuring the transformations' efficacy while maintaining their visual integrity. The combined use of PSNR and SSIM ensures a robust analysis of image quality, balancing both mathematical accuracy and human visual perception.

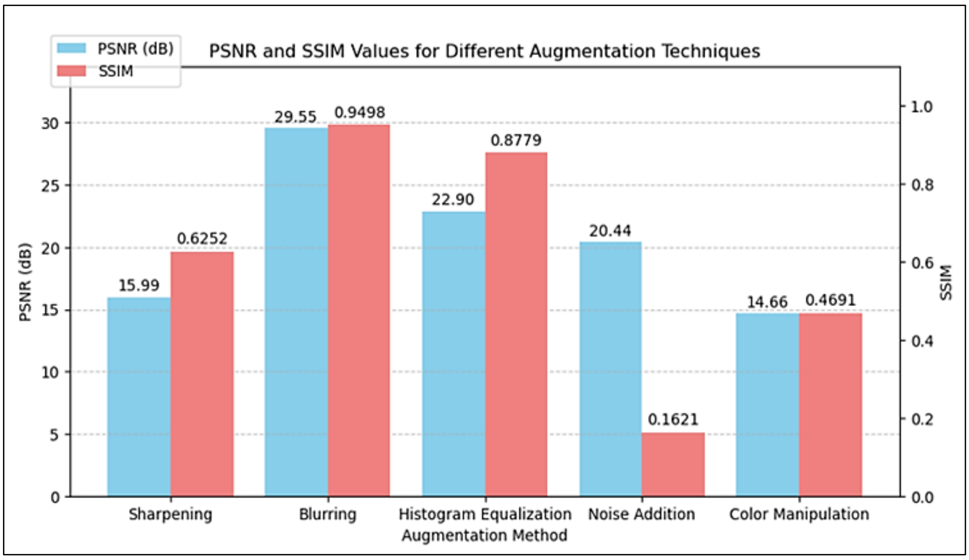


Figure 17: PSNR and SSIM Values for Various Augmentation Methods

The PSNR and SSIM are used to quantitatively evaluate a variety of augmented medical images produced by different methods of augmentation is depicted in Figure 17. The histogram equalization produced the highest PSNR and SSIM measurements, which means that it preserved the structure of the image best, generated better-quality images, while adding noise through augmentation yielded comparatively lower SSIM measurements indicating distortion of the structure of the image due to the added noise.

The mean square error (MSE) of the difference between the expected and actual values in regression analysis or image comparison is referred to as the mean. It quantifies the proximity of predicted values to actual values, offering a straightforward method to assess a model's functioning or the fidelity of generated images. The MSE is determined by aggregating the squared intensity difference of the pixels of the distorted and reference image pixels and the corresponding PSNR (Equation [3]).

$$MSE = 1/N \sum_{x=1}^{N} (a_x - \hat{a}_x)^2 \quad [3]$$

Where,

N - number of observations, a_x - actual value, $\hat{a}_x$ - predicted value.

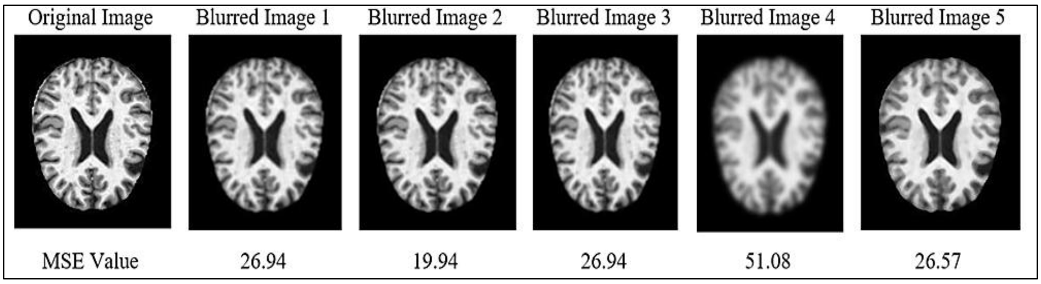


Figure 18: Representation of Mean Square Error Values

Figure 18 displays the corresponding MSEs for different blurred figures, indicating the pixel-level distortion related to augmentation. The greater the image structure preservation, the lower the MSE. It solely the MSE task. Histogram equalization is one of the highly efficient image enhancement technologies. One type of spatial method is histogram equalization. It uses different contrasts in the image histogram to process the image. This increases local brightness. Increasing local contrast does not affect the contrast of the entire image. Two methods are commonly used, such as histogram equalization and profiling (37).

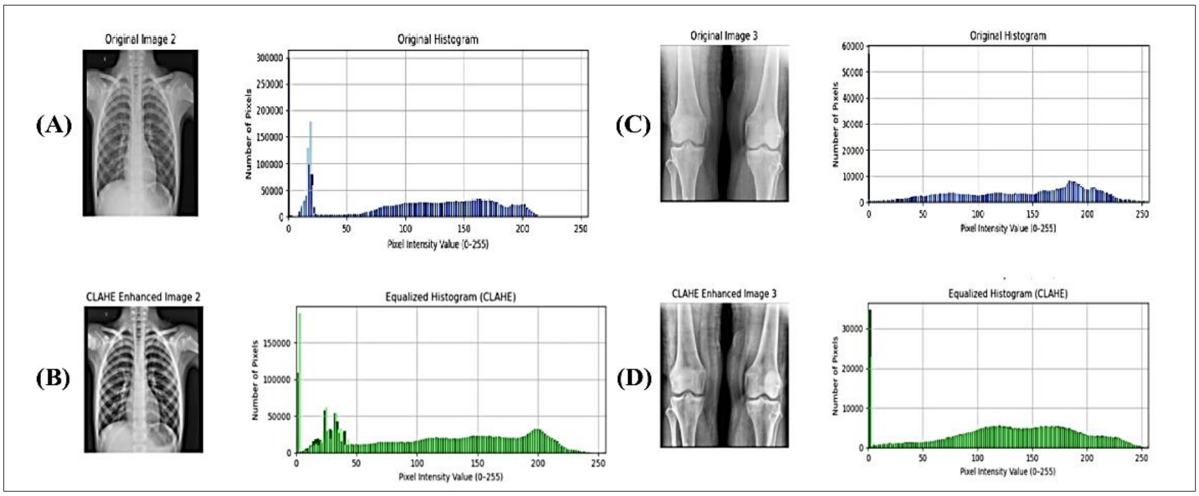


Figure 19: Equalized Histogram for CT and X-Ray Images for Original Image and CLAHE Technique

The original and CLAHE-processed versions of the same long-standing medical imaging study as well as histograms of their respective pixel intensity values were shown in Figure 19. Histogram equalization resulted in greater contrast distribution among the different pixel intensity levels than the results of the CLAHE processing. This indicates that contrast limited adaptive histogram equalization increases the visibility of anatomical structures in the images.

Subjective image quality assessment is a commonly used method of averaging opinion scores, which requires assigning perceived quality scores to image tests. The purpose of this test to evaluate subjective image quality, and Evaluators should assign perceived quality scores to test images (38).

Mean Square Error is a widely accepted indicator of media quality, but it is often applied without adequate consideration of its scope or limitations despite its clear benefits (Equation [4]).

$$MOS = \frac{\sum_{i=1}^{N} S_i}{N} \qquad [4]$$

Where,

S_i is the score given by the i^{th} observer.

N is the total number of observers.

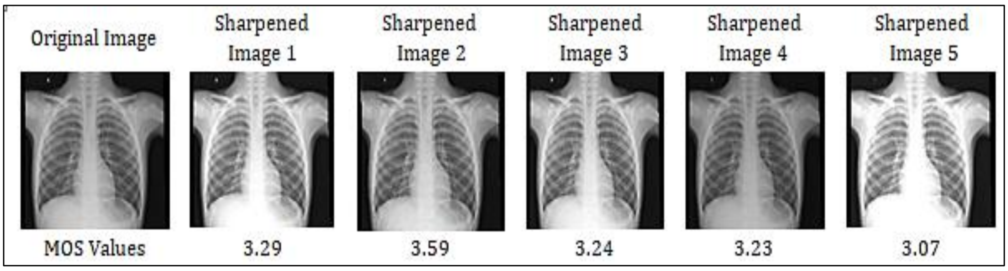


Figure 20: Representation of Mean Opinion Score Values with Sample Images

Figure 20 illustrates chest X-ray images evaluated using the Mean Opinion Score (MOS) methodology. The MOS value assigned to each X-ray is an indicator of how well that X-ray is perceived by the viewer, based upon the viewer's subjective assessment of its visual appearance. Higher scores reflect clearer and higher-quality images than those with lower MOS scores. There are slight variations in contrast, sharpness, and noise between the X-ray images when they are compared side by side. This example demonstrates the use of the MOS to evaluate the quality of medical imaging, showing how MOS indicates the quality of medical images.

A metric used in imaging operations to measure the information content of an image is called entropy measurement (EM) (27). A complex image with a large range of pixel values is indicated by a high entropy number, while a more simple, homogeneous image is indicated by a low entropy value. The quality or complexity of an image can be evaluated using entropy, which can also be used to identify the most instructive areas of an image for additional processing or analysis (Equation [5]).

$$H\ (X) = -\ \Sigma\ (i)\ \log\ (i) \qquad [5]$$

Where,
X is the grayscale image.
P(x) – probability of occurrence of value level j.

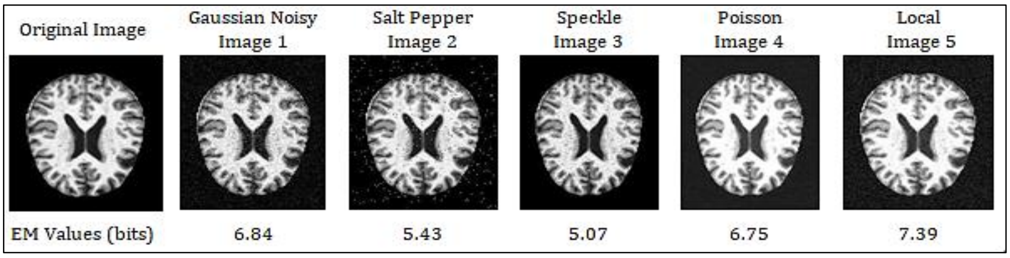


Figure 21: Representation of Entropy measurement values

Figure 21 displays the entropy, or EM of the various noise models (Gaussian, Salt-and-Pepper, Speckle, and Poisson). The amount of randomness or information entropy introduced into the image from each type of noise can be assessed using the measured entropy value. The Local noise model has the most randomised or chaotic appearance, and therefore, its entropic value is the highest out of all the noise models, whereas the Speckle noise model has the lowest entropic value of all five types of noise. Normalized Cross-Correlation (NCC) is one of the most prevalent evaluation metrics in pixel-level transformations, which is used to evaluate similarity between two images; usually these are images before and after transformation (39). NCC measures the resemblance of two images based on their pixel fervour patterns—useful in evaluating how successful transformations like noise addition, blurring, or any other augmentations performed in data preprocessing are. Gray-level images are typically used for traditional NCC-based methods (Equation [6])(40).

$$\text{NCC} = \frac{\Sigma_{a,b}\ (M(a,b) - \underline{M})(N(a,b) - \underline{N})}{\sqrt{\Sigma_{a,b}\ (M(a,b) - \underline{M}\,)^2}\ \sqrt{\Sigma_{a,b}\ (N(a,b) - \underline{N}\,)^2}} \qquad [6]$$

Where,
M (a, b) and N (a, b) are pixel values of the two images at coordinates (M, N).
$\underline{M}$ and $\underline{N}$ - mean values of the images M and N.
The numerator computes the cross-covariance, while the denominator normalizes the values, ensuring the outputs is within the range [-1,1].

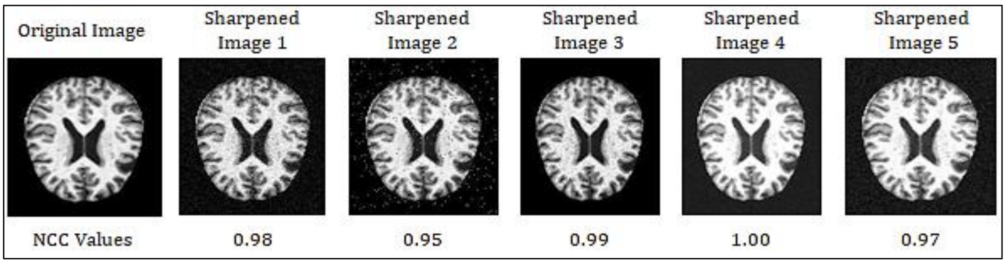


Figure 22: Representation of Normalized Cross-Correlation Values

In Figure 22, the NCC values of the sharpened image throughout all stages were shown. It indicates a large portion of the image's essential structure has been preserved with the application of sharpness and detail enhancements. The sharpened figures were evaluated quantitatively by using Entropy and Normalised Cross-Correlation (NCC). The NCC value varies from 0 to 1, and the higher the NCC value is, the more structurally similar it will be to the original figure. In this evaluation, NCC values larger than 0.95 are defined as highly similar. As observed, the value of

NCC was maximum (1.00) for Sharpened Figure 4, which implied excellent structural preservation, and this was followed by Sharpened Figure 3 (0.99). Even though Sharpened Image 2 has an NCC as high as 0.95, it is relatively low in similarity. The entropy analysis confirms this fact, showing enhanced information content without excess noise amplification.

Conclusion

This paper analyzes the different image data augmentation methods used for augmenting medical images. We experimented with every pixel-level transformation method available to enhance medical images from various imaging modalities. From the experimental work, it was determined that pixel-level transformation techniques may be used as a type of image augmentation to improve image information for developing applications based on DL. Theperformance of image augmentation is demonstrated by the calculated PSNR, SSIM, MSE. Histogram equalization and NCC metrics.

Abbreviations

CT: Computed Tomography, DL: Deep Learning, MSE: Mean Square Error, PSNR: Peak-To-Noise Ratio, SSIM: Structural Similarity Index Measurement.

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Author Contributions

All the authors contributed equally.

Conflict of Interest

The authors declare that there is no conflict of interest.

Declaration of Artificial Intelligence (AI) Assistance

The authors declare no use of AI for the write-up of the manuscript.

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