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Data Augmentation Techniques applied to Medical Images

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ABSTRACT

One of the most well-known methods to improve the performance of a deep learning model is data augmentation. It entails creating new data samples from old ones utilizing conceptual methodologies. There are numerous techniques for implementing data augmentation in the context of image processing, including translation, shearing, rotating images, changing hue, modifying greyscale, creating synthetic images using GAN, etc. Data augmentation is frequently used to boost model accuracy, decrease overfitting, and overcome data shortages, particularly in the field of biomedical image processing. Contrarily, the most well-known deep learning models for image processing, and specifically picture classification, are convolutional neural networks (CNNs). The proposed review aims at throwing a light on the motivation for data augmentation, various techniques used for augmentation as well as analyzing the various studies that make use of data augmentation on medical images such as CT, MRI, Mammograms and Fundoscopy images.

Keywords: Data Augmentation, Medical Image Processing, Deep Learning, Radiomics

1. Introduction

The task of making a computer comprehend the images is a challenge in and of itself, particularly when it comes to medical images like CT, MRI, Ultrasound, X-ray, etc. It is a laborious process to become familiar with it and learn to evaluate what the computer can perceive. Convolutional neural networks with deep learning models could be used to solve this problem and accomplish the objective at hand. Augmentation is a great approach to improve this process and enable a computer to learn more precisely and accurately about the changes that occur in actual images. In many areas of computer science, including computer vision, image classification, recognition of objects, and image segmentation, deep learning has proven to be effective [1-3,5,14,24-27,119]. Large datasets are an essential prerequisite for deep learning models. Different deep learning models are unlikely to be capable of acquiring knowledge and generating accurate predictions without the presence of an extensive amount of images in datasets. Unfortunately, certain fields, such medical image processing, lack access to significant amounts of data. There is no benchmark dataset available at the beginning for some disorders. One of the most prominent instances of the need for data augmentation to improve outcomes based on the limited dataset that exists, is the COVID19 pandemic, zika virus spread etc. [124,125]. The present study provides a summary of the numerous data augmentation methods that can be applied to further improve the volume of images as well as gives the overview of the various studies that have implemented data augmentation and have achieved better accuracy in the tasks of segmentation and classification of medical images.

1.1 Augmentation

Modern deep learning-based classification and diagnostic systems require a tonne of labeled training data to construct an effective system and achieve high accuracy. By enhancing the diversity of the data, data augmentation enables researchers to train their models more effectively with diverse data without having to collect it manually. The amount of data that is accessible has a significant impact on how well deep learning algorithms work. As a result, in order to make up for the paucity of data, several data augmentation techniques are used with the intention of significantly increasing the number of images available [24-27]. As a result, it may be easily acknowledged as an essential approach that, simply by making use of the real data available, effectively expands the sample size.

1.2 Need for data augmentation: Avoid the necessary Evil

The task of obtaining fresh samples of the ground truth becomes crucial where the situation involves a severe lack of actual data. It can be considered as a necessary evil since this necessary task is expensive in terms of cost and time. These issues are frequently encountered especially when working with data related to medicine. In simple words there is scarcity of available data in the medical image processing domain. In order to avoid the necessary evil of manually collecting the data samples, data augmentation comes to the rescue. Data augmentation has proven to be a fruitful method when it comes to expanding the dataset size in certain circumstances [11,44-51,63,75,119]. A few reasons are listed below that are major drivers for data augmentation:

- **Data insufficiency:** The lack of data, notably medical images, for training deep learning models is one of the main reasons for utilizing data augmentation. Fewer datasets are available for medical image analysis since obtaining access to patients' confidential medical records is expensive in terms of labor and time. Patients' consent is required for the creation of medical datasets, and certain additional issues such as data authenticity, security and relevance of the collected data are also to be taken into consideration. Here, the methodologies of data augmentation come to the rescue of the researchers simply by increasing not only the amount but also the quality of the medical data available which is aimed to be kept comparable to the original medical images.

- **Data unevenness:** Overcoming class imbalance also popularly referred to as creating balanced classes of data. It can be considered as a pivotal benefit of data augmentation. In order to carry out the desired tasks which can be detection, segmentation, prediction or classification etc., a balanced and enriched dataset is always preferred. The specific classes of the dataset, in order to have data equitably in all classes involved in the specific task, a wide variety of data augmentation techniques are applied either to a specific class present in the dataset or to the entire dataset which is available at hand.

- **Variation in data:** The expansion of the dataset by applying a wide variety of augmentation methods not only facilitates the expansion of the collection of known data for the particular machine learning or deep learning based model, but also results in bringing about valuable and insightful variation throughout the data. Variation in the data greatly contributes to the model's ability to generalize, which is a highly desired trait when it comes to training deep learning based models.

- **Relaxation to researchers, cost effective and helps to achieve better testing accuracies:** Data augmentation eliminates the requirement for domain specific medical specialists and plays a significant role in generating desirable and well-labeled datasets. Hence becoming highly time and money efficient as it expands the limited dataset at hand artificially with little to no involvement of the labor-intensive process by the researchers and domain specific expertise of manually collecting and processing the data.

- **Implicit Regularization or Solution to the problem of over-fitting:** Without the proper regularization, the majority of deep learning-based models and algorithms frequently encounter the problem of overfitting over the training dataset. Therefore, a number of data augmentation approaches are used with the goal of considerably reducing the issue while also improving the classification, detection, segmentation and prediction etc related tasks performance of the model on the test data, also referred to as the unseen data that resembles the real world scenario. The data augmentation also helps in making the deep learning based model more generalizable, which is a highly desired trait.

1.3 Literature survey

In the literature, augmentation techniques have been applied to the datasets of different tissue images such as MRI of brain, CT scans of chest, mammography of breast and fundoscopy of eye have been studied which involve the implementation of various augmentation methods such as rotation, blurring, flipping, stretching, noise addition, shearing, translation, cropping, shifting and Generative Adversarial Network (GAN) to increase the sample size and improve the performance of different tasks mainly segmentation and classification.

The table 1 focuses a brief description of the augmentation techniques used for the task of segmentation on various medical images. Ronneberger et al.[6] implements shifting, rotation augmentation to enable efficient segmentation in ISBI challenge. Pereira et al.[7] focus only on rotation based augmentation of brain MRI images. Isensee et al., Krivov et al.[8], Hashemi et al.[115], Neelima et al.[114], Cirillo et al.[5], Aswathy et al. [117] and Fidon et al.[104] have applied random scaling, rotation, and elastic deformation to achieve high segmentation accuracy. To generate synthetic images GAN based augmentation has been applied by Kossen et al. [109], Shi et al. [107], Li et al.[102], Sun et al.[103] and Wu et al.[105].

Table 1 A brief description of the augmentation techniques used for segmentation in medical images.

Investigator	Image	Augmentation Technique
Ronneberger et al. (2015)[6]	Leukemia	Shift, rotate
Pereira et al. (2016)[7]	Brain MRI	Rotate
Krivov et al. (2017)[8]	Brain MRI	Random elastic transformations, affine transformations (scale, rotate, reflect), and coregistration-based augmentation.
Isensee et al. (2020)[101]	Brain MRI	Random scaling, rotate and elastic deformation
Li et al. (2020)[102]	Brain MRI	GAN
Sun et al. (2020)[103]	Brain MRI	GAN

Fidon et al. (2020)[104]	Brain MRI	Random rotation, crop, zoom, Gaussian noise addition, blur
Wu et al. (2020a)[105]	Brain MRI	GAN
Yuan (2020)[106]	Brain MRI	Flip, contrast changing
Shi et al. (2020)[107]	Lung CT	GAN
Müller et al. (2021)[108]	Lung CT	Scale, mirroring, elastic deformations, rotate, contrast changing, Gaussian noise addition
Kossen et al. (2021)[109]	Brain MRI	GAN
Cirillo et al. (2021) [5]	Brain MRI	Flip, rotate, scale, brightness adjustment, and elastic deformation
Xie et al. (2022)[110]	Brain MRI	Rotate, flip
Quintana-Quintana et al. (2022)[111]	Brain MRI	Flip, zoom
Liu et al. (2022)[112]	Brain MRI	Crop and flip
Chaki (2022)[113]	Brain MRI	Flip, scale, and rotate
Neelima et al. (2022)[114]	Brain MRI	Translate, flip, rotate, contrast adjustment
Hashemi et al. (2022)[115]	Brain MRI	Translate, flip, shear, scale, rotate
Farheen et al. (2022)[116]	Lung CT	Flip and rotate
Aswathy et al. (2022)[117]	Lung CT	Rotate, translate, shear, and zoom
Kim et al. (2022)[118]	Mammograms	Shift

Note: MRI: Magnetic Resonance Imagining, CT: Computed Tomography, GAN: Generative Adversarial Network

The table 2 focuses on a brief description of the augmentation techniques used for the task of classification on various medical images. In a study by Dufumier et al.[67], image augmentation has been achieved by using the affine transformation such as translation, rotation, random cropping, and photometric transformations such as blurring, and noise addition to achieve desired high performance from the methods applied for the tasks of prediction of age, diagnosis of schizophrenia, as well as the classification of sex. Hu et al.[56] achieves image augmentation by implementing affine transformations such as flipping, translation, rotation, and photometric transformation such as alterations in the brightness for efficacious diagnosis of pneumonia, covid-19. Similarly, Alshazly et al. [62] implements a set of affine as well as photometric augmentation techniques such as Gaussian noise addition, crop, flip, blurr, brightness alterations, shear, and rotation. GAN structures have been implemented by Wang et al.[60] as well as Nishio et al.[57] that efficiently produce synthetic images which show the area with lung nodules and introduce diversity in the sizes of lung nodules. Zeiser et al. [53] includes image refinement by applying noise reduction and resizing of the images followed by the task of segmentation and then applying augmentation techniques such as mirroring, zooming, and resizing. Karthiga et al.[84] focuses on noise elimination before the segmentation of the images. Alyafi et al.[50] includes flipping and GAN based augmentation techniques. GAN based augmentation technique has been used by Wu et al.[52] and Shen et al.[68]. Shyamalee and Meedeniya have used the generic augmentation techniques such as to rotate, shear, zoom, flip, and shift the images. Tufail et al.[73] uses a combined augmentation which includes shifting and blurring. Another study by Kurup et al.[9], focuses on a combination of rotation, translation, mirroring, and zooming. Agustin et al. implements image augmentation by zooming and CLAHE. Zhou et al.[48] and Balasubramanian et al.[47] use GAN models based augmentation.

Table 2 A brief description of the augmentation techniques used for classification in medical images.

Investigator	Image	Augmentation Technique
Frid Adar et al. (2018)[11]	Liver CT	GAN
Han et al. (2019)[4]	Brain MRI	GAN
Khalifa et al. (2019a)[8]	Eye Fundus	Reflect
Kurup et al. (2020)[9]	Eye Fundus	Rotate, translate, mirroring, zoom
Asia et al. (2020)[46]	Eye Fundus	Rotate, flip, scale, clip, and translate

Balasubramanian et al. (2020)[47]	Eye Fundus	GAN
Zhou et al. (2020) [48]	Eye Fundus	GAN
Lim et al. (2020) [49]	Eye Fundus	GAN
Alyafi et al. (2020) [50]	Mammograms	GAN
Agustin et al. (2020)[51]	Eye Fundus	Zoom and CLAHE
Wu et al. (2020b) [52]	Mammograms	GAN
Zeiser et al. (2020)[53]	Mammograms	Mirroring, zoom, and resize
Desai et al. (2020)[54]	Mammograms	GAN
Onishi et al. (2020)[55]	Lung CT	GAN
Hu et al. (2020)[56]	Lung CT	Flip, translate, rotate, and brightness changing
Nishio et al. (2020) [57]	Lung CT	GAN
Loey et al. (2020b)[10]	Leukemia	Shift, rotate
Khalifa et al. (2020)[12]	Chest X-ray	GAN
Loey et al. (2020a)[13]	Chest CT	GAN
Deepak et al. (2020) [58]	Brain MRI	GAN
Barile et al. (2021)[59]	Brain MRI	GAN
Wang et al. (2021)[60]	Lung CT	GAN
Toda et al. (2021)[61]	Lung CT	GAN
Alshazly et al. (2021)[62]	Lung CT	Noise addition, crop, flip, blur, brightness changing, shear, and rotate
Tang et al. (2021) [63]	Lung CT	Rotate, flip
Razali et al. (2021)[64]	Mammograms	Rotate, flip, and shear
Halder et al. (2021)[65]	Lung CT	Rotate, shift, flip
Yashvi et al. (2021)[66]	Chest X-ray	Flip, rotate, translate
Dufumier et al. (2021)[67]	Brain MRI	Translate, rotate, random crop, blur, flip and noise addition
Shen et al. (2021)[68]	Mammograms	GAN
Salama et al. (2021) [69]	Mammograms	Rotate
Mahmood et al. (2021) [70]	Mammograms	Rotate, shrink, shift, flip, crop, contrast and brightness changing
Aly et al. (2021)[71]	Mammograms	Rotate and flip
Li et al. (2021)[72]	Mammograms	Crop and flip
Tufail et al. (2021)[73]	Eye Fundus	Blur and shift
Jha et al. (2022) [74]	Brain MRI	GAN
Srinivas et al. (2022)[75]	Brain MRI	Rotate, shear, flip, crop
Haq et al. (2022)[76]	Brain MRI	Rotate, zoom, brightness change
Nayan et al. (2022)[77]	Brain MRI	Rotate, flip
Tandon et al. (2022a)[78]	Lung CT	Flip, crop, rotate, and shift
Tandon et al. (2022b)[79]	Lung CT	Rescale, rotate, flip

Woan et al. (2022)[80]	Lung CT	Translate, scale, rotate, and flip
Basu et al. (2022)[81]	Lung CT	Rotate, shift, flip
Humayun et al. (2022)[82]	Lung CT	Scale, flip, shear
Dodia et al. (2022)[83]	Lung CT	Translate, scale, flip, brightness change
Karthiga et al. (2022)[84]	Mammograms	Rotate, flip
Ueda et al. (2022)[85]	Mammograms	Rotate, shift, shear, scale, and flip
Miller et al. (2022)[86]	Mammograms	Resize, crop, flip, rotate, and brightness adjustment
Ayana et al. (2022)[87]	Mammograms	Rotate, shift, and flip
Mahmood et al. (2022)[88]	Mammograms	Flip, rotate, translate, and crop
Padalia et al. (2022)[89]	Mammograms	Rotate
Zahoor et al. (2022)[90]	Mammograms	Rotate, flip
Soulami et al. (2022)[91]	Mammograms	Rotate, flip
Sabani et al. (2022)[92]	Mammograms	Shear, zoom, rotate, flip, and brightness changing
Shyamalee et al. (2022)[93]	Eye Fundus	Rotate, shear, zoom, and flip, shift
Li et al. (2022)[94]	Eye Fundus	Rotate, crop, brightness changing
Mayya et al. (2022)[95]	Eye Fundus	Flip, rotate, GAN
Ramya et al. (2022)[96]	Eye Fundus	Translate, stretching, rotate, and flip
Singh et al. (2022)[97]	Eye Fundus	Rotate, crop
Yadav et al. (2022)[98]	Eye Fundus	Rotate, flip, crop, and shift
Lin et al. (2022)[99]	Eye Fundus	Translate, rotate, and flip
Islam et al. (2022)[100]	Eye Fundus	Rotate, flip

Note: MRI: Magnetic Resonance Imagining, CT: Computed Tomography, GAN: Generative Adversarial Network, CLAHE: Contrast Limited Adaptive Histogram Equalization

The table 3 focuses on a brief description of the augmentation techniques used for both segmentation and classification tasks on various medical images. Khan et al. [45] implements augmentation simply by using the addition of noise and sharpening of the images to enhance the accuracy of segmentation and classification whereas Ju et al. [44] focuses on the use of GAN based augmentation of the eye fundus images.

Table 3 A brief description of the augmentation techniques used for both segmentation and classification in medical images.

Investigator	Image	Augmentation Technique
Khan et al. (2021) [45]	Brain MRI	Random rotation, noise addition, zoom and sharpening
Ju et al. (2021) [44]	Eye Fundus	GAN

Note: MRI: Magnetic Resonance Imagining, GAN: Generative Adversarial Network

The Fig. 1 shows the schematic representation of the distribution of studies in the literature that use augmentation techniques for the task of segmentation and classification**.**

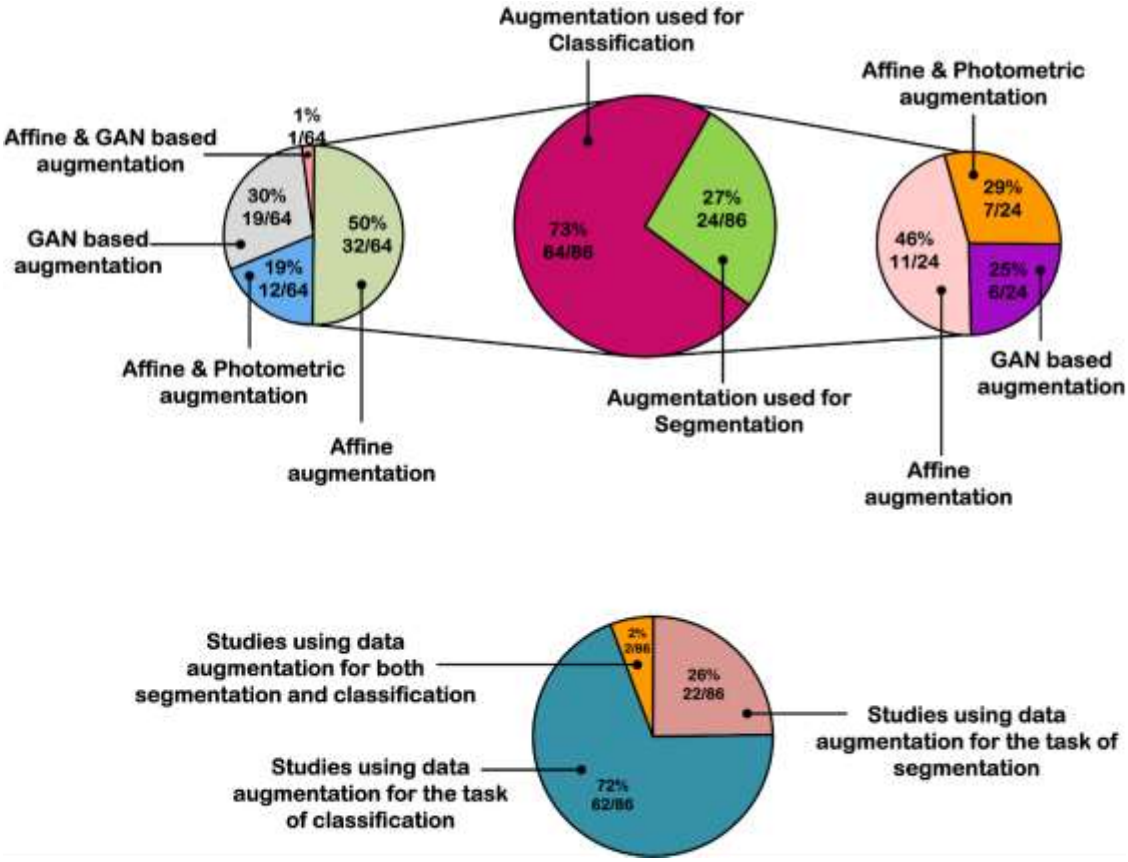

Fig.1 Schematic representation of the distribution of studies that use augmentation techniques for the task of segmentation and classification

1.4 Which dataset to augment?

Dataset in simple words is the set of all the data samples that the researcher plans to use to carry out the current task at hand. This task in terms of image processing can be either segmentation, object detection, prediction, classification etc.. Dataset is nothing but the sample space used to train and test the data model. Here the dataset is the collection of medical images. The dataset is broadly of three types:

Training Dataset: The dataset consisting of the collection of images on which the deep learning based model is trained for various tasks such as classification, segmentation, object detection etc. It usually is preferred to contain the majority of the data samples present in the entire dataset (70-80% of the total dataset).

Testing Dataset: The dataset consists of the collection of images on which the deep learning based model is tested for the task for which it was trained, which can be segmentation, classification, object detection etc. It is usually preferred to contain a minority of the data samples present in the entire dataset (20-30% of the total dataset).

Validation Dataset: The dataset consisting of the collection of images on which the deep learning based model is validated during training. It is usually preferred to contain a minority of the data samples present in the training dataset and is of a small sample size (10-15% of the training dataset).

The Fig.2 shows the different types of dataset and how they are preferably divided by researchers while training their deep learning based models.

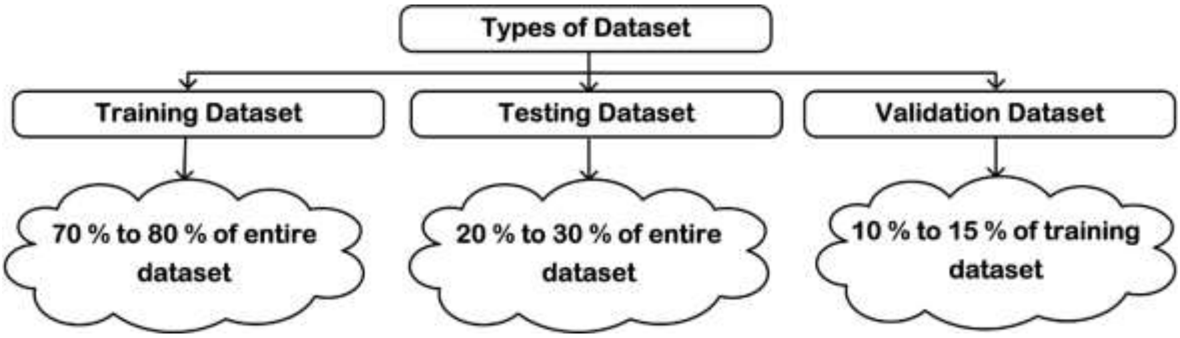

Fig.2 Schematic representation of types of dataset

With the goal to enhance the overall sample size of the accessible dataset, augmentation is used. For the sake of generalized training of the defined deep learning-based system or network and attain robust training and minimize overfitting, a large dataset is recommended. Therefore, a bigger sample space is needed in order to train the system. In contrast, the goal of the test dataset is to identify any discrepancies that the system's developers anticipate it would encounter in real time. As a consequence, the test data ought to be as realistic as achievable. Since there is at present no incentive for expanding the test dataset sample size because the necessary optimal parameters for the model have already been made accessible, performing augmentation on the test data would be a waste of both precious resources and time as well. The expansion of the test dataset frequently leads to unnecessary alterations in class labels, which can impair the trained model's ability to predict outcomes accurately. These arguments support the idea that, in most situations, data augmentation is advantageous when used with training datasets alone.

2. Choosing the right Technique

While processing medical images certain features are considered to be diagnostically significant. These features differ from tissue to tissue and are to be preserved at all costs in order to correctly diagnose or identify the disease related to that specific tissue. When applying data augmentation techniques to medical images, the original class labels and the diagnostically relevant attributes specific to a particular tissue are preserved. Given that a significant portion of medical images involve well-defined solutions from a top-down approach, unlike the bottom-up nature of natural images, the augmentation methods commonly used for natural images might not yield the same level of effectiveness for medical images. Different characteristics are regarded clinically significant and essential for diagnosis for different tissue types. Texture, shape, and color traits are the ones that are crucial for diagnosis.

The texture features are diagnostically significant by the radiologists when dealing with tissues related to brain and liver [23, 29-31, 34]. A combination of texture and shape features are primarily taken into consideration as diagnostically essential when dealing with tissues related to lungs, breast, heart, eye etc[28, 34-40]. When considering histopathology images, a combination of color and texture features are considered diagnostically essential [21,22]. Similarly when dealing with blood smear images a combination of texture, color and shape are considered diagnostically essential [41-43].

2.1 Types of Data Augmentation Techniques

Medical image processing is one of the prime domains for the deployment and implementations of deep learning based models. This has been fueled by the recent development in the field of artificial intelligence, its application in medicine, radiomics, radiotherapy, radiological imaging and most importantly the digital representation of the medical records. The prime difficulty with the implementation of these deep learning based models is that they primarily require a lot of data to be trained on. The creation of image datasets specific to medical images is a challenging task in itself. Hence undertaking such a challenge calls for the involvement of medicine professionals, ample time for dataset annotation, and consideration of issues like patient consent, privacy of patients, and medical record confidentiality. In this situation, data augmentation is crucial in creating novel, optimally labeled data from the pre-existing original data with an aim to expand the existing dataset for the task of training the models to deliver generalized results whilst perpetuating desirable performance.

A variety of approaches, among which are traditional augmentation techniques also referred to as geometrical transformation techniques, then comes the color based alteration techniques that include intensity-based methods, color based methods, spline interpolation, gaussian noise, hue jittering, etc. [15-20]. The data augmentation methods can be considered to be of two types firstly based on the type of augmentation techniques, secondly based on the time of augmentation. The first category that refers to the type of technique used is discussed further. Whereas the second category which is related to the moment in time at which augmentation methods are applied to the existing data is classified as online augmentation and offline augmentation. Online augmentation, also known as augmentation on the fly, is when the data is augmented right before it gets sent to the network and is frequently chosen for datasets that are bigger in size. The other method called the offline data augmentation involves prior augmentation of the data and smaller datasets benefit from this augmentation because they are simpler to manage manually [1-3,5,14,24-27,66]. The Fig. 3 shows the diagrammatic representation of the types of data augmentation techniques.

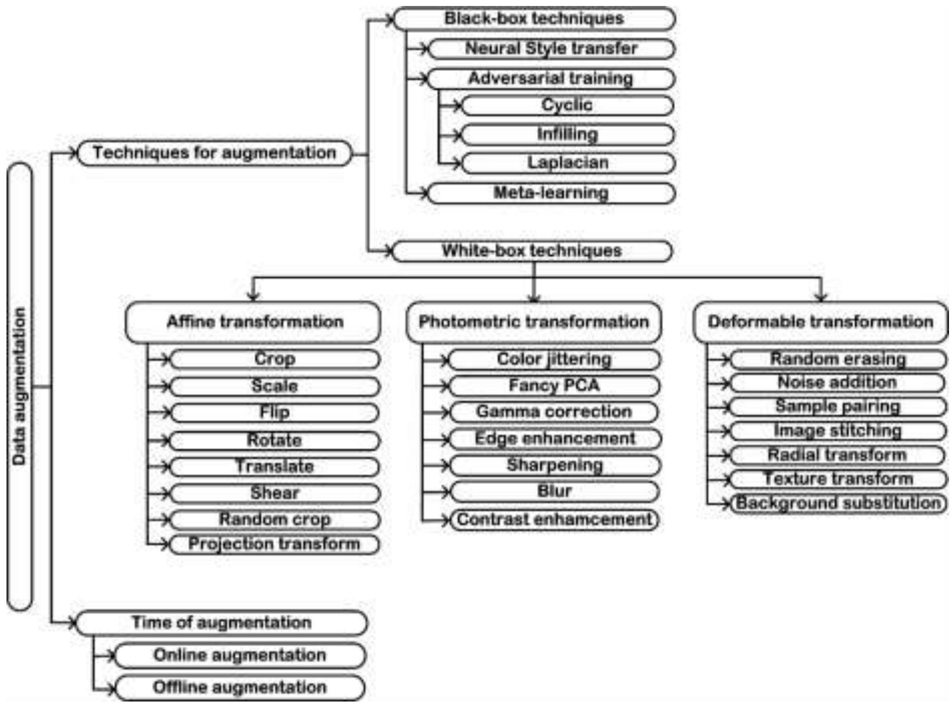

Fig.3 Schematic representation of the types of data augmentation techniques

2.1.1 Generic Augmentation Techniques

It includes techniques that are generic in nature and are popularly known as "white-box techniques". The white-box augmentation methods focus on augmenting the original images with the prime aim of retaining their labels. It broadly consists of the following three types of augmentation methods:

Types of Affine Data Augmentation Techniques

This is the most conventional type of augmentation technique and is commonly performed. It is popularly referred to as geometric transformations. It includes zooming or scaling, shearing, reflection or flipping, rotation, translation or shifting, random crop or cropping etc.

The Fig.4 shows the different geometrical transformation that can be applied to the chest x-ray.

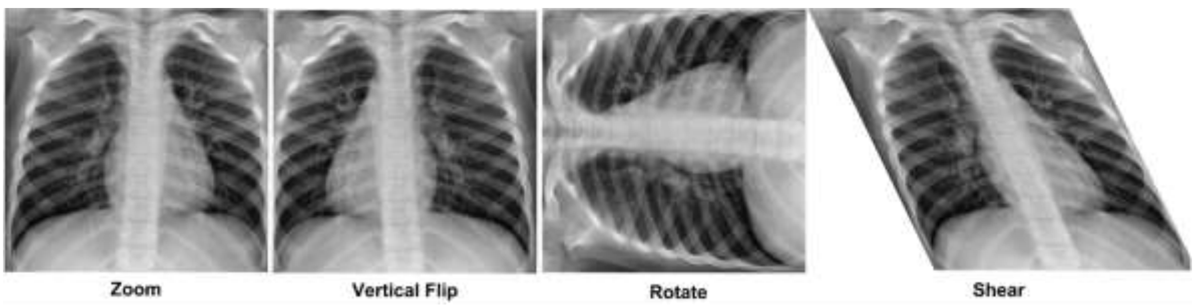

Fig.4 Affine Data Augmentation Techniques on Chest x-ray

(*a*) Rotate: One of the most popular and regularly utilized augmentation methods, particularly in medical imaging, is geometrical augmentation. With the exception of the scenarios when the features of the image heavily depend on the orientation of the object, the image is rotated at a specific angle. It is done by rotating the image at an angle of to the right or left of the axis. It follows the given equation:

Where θ is varied between 1º to 359º (since rotating at 0º and 360º will result in an image that will represent the original image itself, adding same image to the dataset will increase the bias and negatively affect the results) with desired intervals of 1º, 2º, 5º, 10º etc.. Since an interval of 1º or 2º between each rotation is very less and results in more or less the same image as the original, therefore higher intervals are chosen to generate substantially diverse data.

(*b*) Translate: This method entails shifting image pixels along the four possible directions on the axis: right, left, upward, or downward. By introducing positional variability into the dataset, this approach aids in mitigating positional bias within the existing data. Given that a substantial portion of the original images within the dataset are centrally positioned, the resultant trained model would excel in handling centered images. Translation significantly contributes to enhancing the system's resilience. Following the translation of original images, the maintenance of spatial dimensions is achieved by populating any vacant space with either a constant value ranging from 0 to 255 or random Gaussian noise. The diagram illustrates the translation of a chest x-ray image towards both the right and left sides of the axis[120,121].

(*c*) Flip: This geometrical transformation involves transforming the image either vertically or horizontally by simply flipping them about the axis. It is one of among the most often used and simplest augmentation techniques and is frequently referred to as "mirroring or reflection". This commonly employed augmentation strategy retains the labels of the original dataset while generating fresh samples to enrich the existing dataset. However, this augmentation approach may not be suitable in cases where the characteristics of features are significantly impacted by the spatial arrangement of tissue in the original image. This particularly holds true for features related to unilateral organs or tissues – those present on only one side of the human body. Relocating such features would alter the way the original data was annotated. Notable examples of unilateral organs include the pancreas and spleen. This technique is frequently applied to augment skin images [26,120,122]. The Fig.5 shows the Vertical and Horizontal flip on Chest x-ray image.

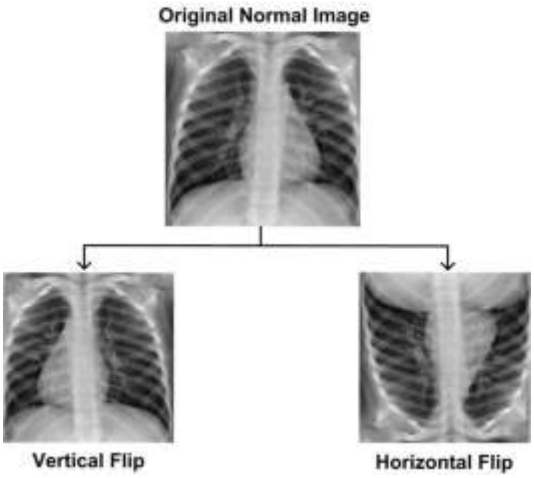

Fig.5 Vertical and Horizontal flip on Chest x-ray image

(c) Crop: Cropping is a technique where patches are randomly selected from an existing image. These random patches are then added back into the dataset to increase the size. This technique is typically used when there is a class imbalance. Patches are generated from the underrepresented class to even the balance [1-3,5,123]. Utilizing cropping of images can serve as a pragmatic preprocessing technique for image data that possesses varied height and width dimensions. This involves extracting a central segment from each image, thereby aiding in standardizing the data. Furthermore, an alternative approach involves random cropping, which closely emulates translations, yielding a comparable outcome. However, it's important to distinguish between random cropping and translations. While cropping leads to a reduction in input dimensions (e.g., from 256x256 to 224x224), translations maintain the image's spatial parameters. The choice of the cropping reduction threshold becomes pivotal, as it can impact the preservation of image labels during this transformation [121].

(d) Shear: Shearing refers to the alteration of the original image along both the x-direction and the y-direction. It serves as an effective method for modifying the shape of objects within an existing image. Shearing encompasses two distinct forms: the initial form occurs along the x-axis, and the subsequent form operates along the y-axis. The Fig.6 shows the equation for shearing along the x-axis and y-axis [120-123].

$$\begin{bmatrix} f_x \\ f_y \end{bmatrix} = \begin{bmatrix} 1 & shX \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \qquad (1)$$

$$\begin{bmatrix} f_x \\ f_y \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ shY & 1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \qquad (2)$$

Fig.6 Equation (1) demonstrates the application of shearing along the x-axis, whereas Equation (2) illustrates the shearing along the y-axis. In these equations, fx and fy represent the new pixel positions after the shearing process, while x and y correspond to the coordinates of the image.

(e) Scale: Scaling is a technique that modifies an image's dimensions to introduce diversity and variability into the dataset. By presenting the same content in different sizes, scaling adds variations that enhance a model's ability to adapt to changes in object size and image resolution. However, it's crucial to exercise caution in applying scaling. Excessive scaling can distort images and create unrealistic results that don't contribute effectively to model generalization. Striking the right balance in scaling intensity and selecting appropriate interpolation methods is essential to ensure augmented images remain meaningful and representative of real-world scenarios.

Scaling involves adjusting an image's size, encompassing both enlargement (upscaling) and reduction (downscaling) of its dimensions. Through scaling, images can be made larger or smaller while maintaining their original aspect ratio. This process introduces diversity to the dataset, aiding machine learning models in accommodating various object sizes and resolutions [14,24-26,121,123].

On the other hand, zooming specifically refers to magnifying or reducing the view of a portion within an image. It's a visual effect that provides the illusion of bringing an area closer or moving away within an image. Zooming doesn't necessarily entail changing the image's overall size or resolution but influences the level of visible detail. Zooming effects can be achieved using scaling, especially through upscaling to focus on a specific image region. However, while scaling encompasses both enlargement and reduction, zooming typically emphasizes image details without altering the overall image size.

Types of Photometric Data augmentation techniques

Image data, especially digital image, is commonly encoded as a tensor with dimensions (height × width × color channels). An effective approach for augmentation involves making changes within the color channels. This technique is practical and straightforward to implement. Image data is stored in three stacked matrices, each representing pixel values for an RGB color. Basic color augmentations include isolating a single color channel, such as Red, Green, or Blue. By extracting the matrix of a chosen color channel and adding two zero matrices from the other channels, an image can be quickly represented in that single channel. Moreover, simple matrix operations enable easy manipulation of RGB values, allowing for brightness adjustments[24,26,121,123].

The challenges in image processing often stem from lighting biases. For images that are too bright or dark, a quick solution involves adjusting pixel values by a constant while iterating through images. Splicing out individual RGB color matrices or constraining pixel values to specific minimum or maximum values are other rapid color space modifications. Often known as Photometric transformation. It is also a type of generic augmentation method along with affine and deformable but this technique is applicable to color images. It needs to be used carefully as it may cause degradation of the diagnostically desirable features in the image thereby generating images that are of no use. This technique therefore can be sometimes detrimental to the features of medical images that are diagnostically essential. The transformations such as hue or color jittering, hue enhancement, edge enhancement, Gamma correction, PCA based augmentation, sharpening and blurring of images etc. come under this category of data augmentation techniques. More sophisticated color augmentations stem from creating a color histogram that characterizes an image. Altering intensity values in these histograms leads to changes in lighting, akin to what's found in photo editing software.

The realm of color space augmentation offers room for creativity. Modifying the color distribution of images can effectively address lighting challenges encountered in testing data. The Fig.7 shows different photometric augmentation techniques applied by Mikołajczyk et al. [26] on skin lesion images.

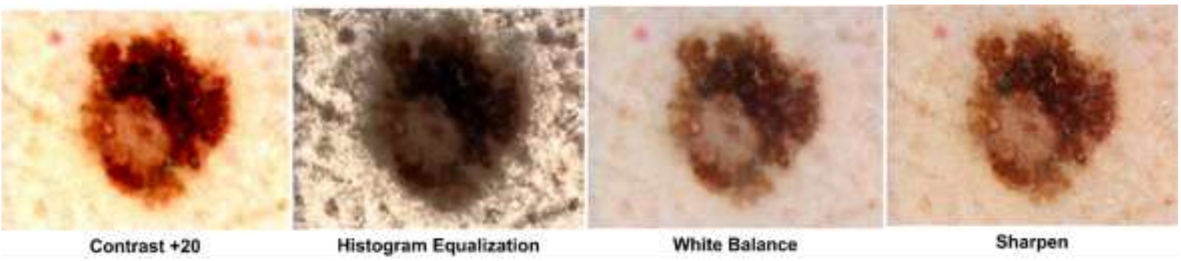

Fig.7 Photometric augmentation by Mikołajczyk et al. [26]on skin lesion images

(a) Color Jittering: Color pertains to the overall visual interpretation of an object or light source, shaped by various characteristics like hue, saturation, and brightness. It encapsulates the complete array of visual encounters linked to distinct light wavelengths. Conversely, hue explicitly signifies the color attribute that separates one hue from another on the color wheel. Hue is established by the predominant light wavelength perceived by the human eye. It stands as the foundational essence of color and is frequently utilized for classifying and depicting colors. While hue stands as a crucial element of color, color is a more inclusive term encompassing supplementary traits beyond hue, such as saturation (color intensity or purity) and brightness (light or dark quality of color).

Hue jittering encompasses the process of introducing controlled randomness to the hue values of pixels by applying slight shifts within a predetermined range. This controlled variation adds diversity to the data without causing significant changes to the core attributes of the object depicted in the image. However, achieving a delicate equilibrium is crucial: excessive jittering could render the image implausible, whereas insufficient jittering might not furnish the model with the necessary range of diverse examples for optimal learning[1-5,24,26,123].

Intensity operations involve altering the pixel/voxel values within an image, frequently achieved by adjusting the image's brightness or contrast. Techniques such as gamma correction, linear contrast adjustment, and histogram equalization are commonly used to modify the image's contrast.

The objective of utilizing hue jittering is to bolster the resilience and variety of a dataset, specifically in machine learning undertakings such as image classification, object detection, or segmentation. Through subtle adjustments to the hue of pixels, while maintaining the constancy of the other color attributes (saturation and value/brightness), the algorithm gains a greater capacity to accommodate shifts in lighting circumstances, diverse color renderings, and other influences that could impact how the color of an object in an image is perceived.

(b) Image enhancement:

Image enhancement encompasses the application of diverse transformations and modifications to images, aiming to enhance their quality, visibility, and overall visual appeal. The primary objective of image enhancement is to enhance the visual attractiveness and informational value of the image, all while maintaining its original context and inherent features. When employed as a data augmentation strategy, image enhancement is instrumental in broadening and enriching the training dataset for machine learning models, especially in tasks like image classification, object detection, and segmentation. One method of filtering an image is carried out through convolution. This involves sliding a convolutional kernel across the image to adjust the pixel intensities at each location based on the neighboring pixel values. This technique enables the production of augmented images by sharpening, blurring, smoothing, and even enhancing the edges of objects within the image. Modifying the image's brightness and contrast can render it more visually impactful and unveil finer intricacies. By adapting the intensity of pixel values, the model can gain better proficiency in managing images exhibiting diverse lighting conditions. Histogram equalization is another technique that redistributes pixel values, enriching overall contrast and detail within an image. This proves particularly valuable for enhancing object visibility in images with suboptimal lighting conditions. Gamma correction, on the other hand, adjusts pixel values to counter non-linearities in brightness levels. It's commonly employed to enhance the appearance of images captured under varying lighting conditions. Meanwhile, employing blur or smoothing filters serves to mitigate noise and elevate image details, resulting in clearer representations. In essence, image enhancement offers a potent approach to augmenting data, where transformations and adjustments not only amplify visual appeal but also foster improved model generalization and performance across a spectrum of real-world scenarios [26,34,86,89,113,119-123].

Types of Deformable Data augmentation techniques

It focuses on deformation of the existing image either by noise addition, radial transform, texture transform, image stitching, spline interpolation, random erasing etc. These techniques do not provide extensive variation in the existing data, as for medical images it is sometime considered favorable since they can deliver images that may contribute in certain tissue deformation related disease diagnosis[1-5,26,119-123]

(a) Random erase: Random erasing stands as another intriguing technique within Data Augmentation, devised by Zhong et al. Drawing inspiration from dropout regularization's mechanisms, random erasing can be likened to dropout, albeit applied in the realm of input data rather than being embedded within the network architecture. This approach was specifically crafted to address challenges in image recognition that stem from occlusion – situations where certain parts of an object are obscured. Random erasing counteracts this by compelling the model to discern more descriptive features in an image, thus preventing it from excessively fixating on specific visual attributes. Beyond just handling occlusion-related visual difficulties, random erasing exhibits promise in ensuring that the network attends to the entire image, rather than focusing solely on a subset. Random erasing operation entails selecting a randomly sized $n \times m$ patch from an image and masking it with either 0s, 255s, mean pixel values, or random values. Essentially, random erasing constitutes a Data Augmentation approach geared toward tackling overfitting by manipulating the input space. By removing specific input patches, the model is coerced to identify alternative descriptive characteristics. This augmentation method can be combined with other techniques like horizontal flipping or color filters to further enhance its effectiveness[1-5, 26, 119-123].

(b) Image stitching: Image stitching can be a valuable technique for augmenting data in the field of medical imaging. Medical image stitching involves the fusion of multiple medical images, such as MRI or CT scans, to construct a more expansive and comprehensive composite image. However, blending images by averaging pixel values might seem counterintuitive for Data Augmentation. Such merged images might not appear beneficial to human observers. Nonetheless, Inoue showcased how the fusion of samples could be transformed into an effective augmentation strategy. Their experiment involved randomly cropping two 256×256 images to 224×224, followed by horizontal flipping. These processed images were then combined through pixel value averaging for each RGB channel. The outcome was a composite image utilized for training a classification model, with the label assigned matching that of the initially selected image[120-123].

In the medical realm, image stitching holds potential for generating larger, more intricate images that offer a broader analytical context. This can be particularly valuable when a single image fails to capture the entirety of a specific area of interest. By merging medical images acquired from distinct angles or slices, precision in localizing objects or anomalies within the body can be heightened, thereby aiding in medical diagnosis and treatment planning. Additionally, medical image stitching can produce more intricate and varied images, thereby challenging deep learning models to excel in intricate medical scenarios and enhancing their accuracy. Moreover, merging images with diverse lighting conditions or varying color balances can infuse variability into the data, bolstering the model's resilience to real-world changes. Nonetheless, the process of image stitching also presents challenges, encompassing image alignment, distortion correction, and preservation of quality and precision, all of which must be diligently addressed in medical settings to ensure the reliability and accuracy of the augmented data. [113]

(c) Noise addition: Noise injection stands as a widely adopted method for augmenting data, aiming to replicate images with noise-like qualities. Gaussian noise injection is the most prevalent, involving the alteration of image intensities by drawing samples from a Gaussian distribution in a random manner. Uniform noise, which adjusts values through random sampling from a uniform distribution, and salt and pepper noise, wherein pixels are randomly altered to black or white, have also found application [120-123]. Noise injection encompasses introducing a matrix of random values, usually obtained from a Gaussian distribution. This augmentation technique involves the deliberate introduction of controlled noise, such as Gaussian or speckle noise, into an image. This process effectively emulates real-world inconsistencies and variations, thereby bolstering the model's adaptability to noise within test data.

(d) Spline Interpolation: Spline interpolation is a mathematical technique that employs segmented polynomial functions to approximate values between existing data points. It often produces more accurate outcomes compared to simpler methods like linear interpolation. When utilized for deformable image augmentation, it provides a way to compute a seamlessly distorted image, effectively generating novel image data. The predominant splines employed are B-splines and thin plate splines [119-123].

2.1.2 AI based Augmentation Techniques

It includes complex AI driven data generation methods and such techniques result in the generation of synthetic data. These are popularly known as "black-box techniques". This synthetic data is added to expand the existing original dataset. Some of the Black box augmentation methods are as follows:

(a) Neural Style: It is a method of augmenting data in which the style of one image is combined with the subject matter of another image with the intention of recreating the input image as its subject matter but with the style of reference of the other image [119-123].The Fig.8 shows neural style data augmentation technique implemented by Mikołajczyk et al. [26] on skin lesion images.

Fig.8 Neural style data augmentation implemented by Mikołajczyk et al. [26] on skin lesion images

(b) Adversarial Training: It makes the use of generative adversarial networks (GAN). It includes cyclic GAN, style-based GAN, guided GAN etc. While performing a GAN based augmentation of chest images, specifically CT images of lung tissue, the researchers mainly focus on the generation of the lung nodules area in the entire image. Since the lung nodules are smaller and hence it results in a cost-effective technique in comparison to generating a larger whole image which includes the lung along with the background setting. Adversarial training functions as a data augmentation method that employs a type of generative modeling to enrich the variety and resilience of a machine learning model's training dataset. The approach involves introducing a secondary network referred to as a "generator" or "adversary." This generator generates synthetic data samples with the intention of mimicking the characteristics of the original training data. The primary objective of adversarial training is to educate the primary model, often termed the "discriminator" or "classifier," to accurately differentiate between actual and synthetic data. Concurrently, the generator is trained to generate synthetic data that closely emulates real data, thereby deceiving the discriminator effectively [48,50,54,58,68,103,114,119,123]. The Fig.9 shows diagrammatic representation of adversarial training.

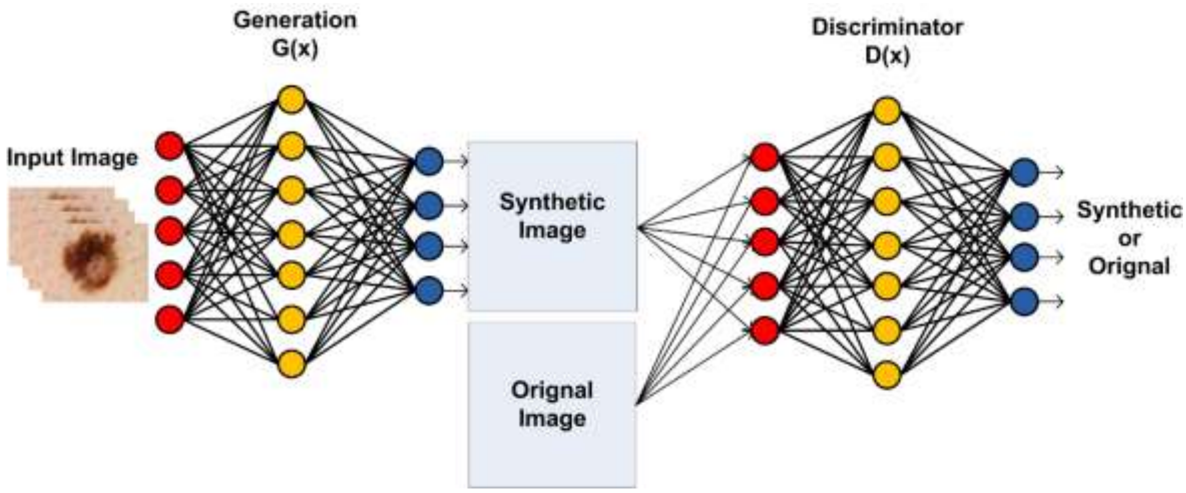

Fig.9 Schematic representation of adversarial training

The process of adversarial training unfolds as follows:

1. **Discriminator Training:** The principal model, frequently a neural network, is trained using both real and synthetic data instances. Its role is to aptly classify whether an input is genuine (originating from the original dataset) or synthetic (generated by the generator).

2. **Generator Training:** In parallel, the generator network is trained to create synthetic data that can mislead the discriminator into classifying it as authentic. The generator strives to comprehend the patterns and attributes of the original data in order to generate samples that are nearly indistinguishable from genuine data.
3. **Iterative Process:** The training procedure alternates between refining the discriminator's capacity to differentiate real from synthetic data and enhancing the generator's ability to generate more convincing synthetic data. This iterative process persists until the generator generates data that is challenging for the discriminator to differentiate from real data.

Essentially, adversarial training transforms data augmentation into a competition between the discriminator and the generator. The generator's objective is to generate samples that progressively resemble real data, while the discriminator hones its capability to differentiate between authentic and synthetic data. As this iterative training unfolds, the generated data becomes more varied and increasingly mirrors authentic data. Ultimately, the discriminator evolves into a more robust classifier, and the generator generates data that effectively expands the training dataset. Adversarial training proves especially valuable for generating samples in domains where obtaining substantial and diverse authentic data is complex. This technique has been successfully applied across various domains, including computer vision, natural language processing, and healthcare, to enhance model performance and the ability to generalize by effectively augmenting the training dataset with high-quality synthetic data [4,11,13,48,50,52,54,58,68,103,114, 119,123].

(c) Meta-learning: Meta-learning in the realm of Deep Learning research generally pertains to the idea of optimizing neural networks using other neural networks. Meta-learning, also referred to as "learning to learn," is an advanced data augmentation approach that centers on training a model to swiftly adapt and generalize to novel tasks with minimal data. Rather than exclusively enhancing performance on a specific task, the focus of meta-learning is on bolstering a model's capacity to efficiently acquire knowledge from limited data, a valuable attribute especially in scenarios where data is scarce or costly to procure. The potency of meta-learning arises from its emulation of the human learning process, where prior knowledge and experiences expedite the grasp of new concepts. Similarly, meta-learning furnishes a model with the competence to effectively extrapolate to new tasks with scant data. This technique proves particularly advantageous in situations where amassing an extensive annotated dataset for each task is unfeasible or resource-intensive. Meta-learning's applications span a range of domains, including computer vision, natural language processing, and robotics. It elevates model adaptability, mitigates the demand for voluminous task-specific data, and empowers models to deliver commendable performance in scenarios constrained by limited data availability[24,119,123].

3. Conclusion

This review highlights that data augmentation has predominantly been utilized in tasks centered around classification and segmentation, leading to substantial accuracy improvements in deep learning models. The augmentation methods most frequently employed include affine augmentation and fundamental geometric transformations like rotation, flipping, and translation. Many research studies have showcased the adoption of augmentation techniques based on Generative Adversarial Networks (GANs) to generate synthetic data, thereby enriching dataset diversity and resilience.

Some of the most common data augmentation techniques used in medical image processing include:

1. **Rotation and Flipping:** Rotating images by certain angles (e.g., 90, 180 degrees) and horizontally or vertically flipping them helps introduce variations while maintaining anatomical consistency. This is particularly useful for radiological images like X-rays and CT scans.
2. **Translation:** Shifting images along the horizontal and vertical axes can simulate changes in patient positioning during imaging. It helps create variations while preserving spatial relationships.
3. **Scaling and Resizing:** Changing the size of images by scaling them up or down introduces variations in image resolutions and helps models generalize to different image sizes.
4. **Elastic Deformations:** Applying elastic deformations involves applying local distortions to the image grid, mimicking the deformations that might occur due to patient motion or tissue deformation.
5. **Intensity Adjustments:** Manipulating pixel intensity values by changing brightness, contrast, and gamma can simulate variations in lighting conditions and enhance visibility of certain features.
6. **Noise Injection:** Adding noise, such as Gaussian or speckle noise, to images mimics the imperfections often present in medical imaging due to acquisition processes.
7. **Crop and Padding:** Cropping a region of interest from an image or adding padding around it can help focus on specific areas and simulate variations in object positioning.
8. **Histogram Equalization:** This technique redistributes pixel intensity values to improve contrast, which can be particularly useful for enhancing details in medical images with uneven lighting.
9. **Geometric Transformations:** Applying affine transformations, such as shearing or scaling, can mimic distortions in medical images due to non-uniform deformations.
10. **Superimposition of Artifacts:** Adding simulated artifacts, like simulated noise patterns, to images can help models learn to identify and handle artifacts that might be present in real medical images.

11. **Domain Adaptation:** Utilizing techniques like style transfer or domain adaptation to adapt images from one modality or source to another can enhance cross-modality generalization.
12. **Sliced Data Augmentation:** For 3D medical images, techniques like random slicing or interpolation between slices can be used to augment volumetric data.

Conflict of Interest Statement

The authors declare that they have no conflict of interest in the work presented in this paper. No financial support or sponsorship was received from any organization or individual that could influence the outcome of the present work.

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