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SURVEY

A review of deep learning and Generative Adversarial Networks applications in medical image analysis

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Abstract
Nowadays, computer-aided decision support systems (CADs) for the analysis of images have been a perennial technique in the medical imaging field. In CADs, deep learning algorithms are widely used to perform tasks like classification, identification of patterns, detection, etc. Deep learning models learn feature representations from images rather than handcrafted features. Hence, deep learning models are quickly becoming the state-of-the-art method to achieve good performances in different computer-aided decision-support systems in medical applications. Similarly, deep learning-based generative models called Generative Adversarial Networks (GANs) have recently been developed as a novel method to produce realistic-looking synthetic data. GANs are used in different domains, including medical imaging generation. The common problems, like class imbalance and a small dataset, in healthcare are well addressed by GANs, and it is a leading area of research. Segmentation, reconstruction, detection, denoising, registration, etc. are the important applications of GANs. So in this work, the successes of deep learning methods in segmentation, classification, cell structure and fracture detection, computer-aided identification, and GANs in synthetic medical image generation, segmentation, reconstruction, detection, denoising, and registration in recent times are reviewed. Lately, the review article concludes by raising research directions for DL models and GANs in medical applications.

Keywords Deep learning · Generative Adversarial Networks (GANs) · Synthetic data · Data augmentation · Computer aided decision support system (CADs) · Medical images

1 Introduction

In the medical care and management system, there is a substantial increase in medical images. There are different imaging modalities like Ultrasound images, Mammography Images (MG), X-Rays, Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), Magnetic Resonance Angiography (MRA), pathological tests, etc. It is often difficult and time-consuming to analyse medical images [1].

Deep learning (DL) models can address the problem of medical image analysis. Deep learning is an application of Artificial Intelligence that can learn from the input data and make decisions or predictions depending on the training data. There are three learning methods: unsupervised learning, supervised learning, and semi-supervised learning. Extraction of features is needed in the machine learning algorithms, and specific problem-related feature selection requires the help of a domain expert. Deep learning algorithms are a part of machine learning that automatically

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extract the necessary features from the input data [2]. Most of the review papers are on the capabilities of deep learning algorithms in the medical fields of radiology [3], MRI [4], Neurology [5], and Cardiology [6]. For object detection, segmentation, and classification of medical images, Convolutional Neural Networks (CNN) are used in deep learning [7, 22]. The collection of medical images requires a lot of effort. Even with high effort, if the data collected, the labelling and annotation of the data require the help of the doctors. The unavailability of a large collection of images of the same disease is another problem. Recently, GANs have been extensively used for the synthesis of medical images. The synthetic images from GAN aid in overcoming the problems of privacy, low data set size, imbalanced data set, etc. Rotation, scaling, flipping, and translation are traditional augmentation methods. These traditional augmentation methods result in changes in the shape, location, and size of images. The GANs generate realistic images and are used to augment the training images with good outcomes in medical applications. The main objective of this work is to review the recent use of deep learning models, or GANs, in different medical image analysis. The paper is organised as follows: Sect. 2 deals with different applications of deep learning models in the medical field; Sect. 3 deals with deep learning-based generative models and their applications in the medical field; followed by discussion and conclusion in Sects. 4 and 5.

2 Different applications of DL model in medical image analysis

In the development of modern deep learning, techniques like Lenet and AlexNet were frequently used. Subsequent network architectures are substantially more complicated, with each generation building on ideas and insights from prior systems, producing in state-of-the-art improvements. The prominent basic building CNN architectures described below:

AlexNet [34] employed an eight-layer network structure with three fully connected layers and five convolutional layers. The maximum pooling technique is used to minimize the quantity of data after each convolution in the five convolutional layers. The input size for AlexNet is 227×227 pixels. Use of RELUs, dropout regularization, dividing the computation across many GPUs, and data augmentation during training are notable aspects.

Oxford University's VGG Group first proposed VGG16. The larger convolution kernels in AlexNet, such as 11×11 and 5×5, are replaced by a series of sequential 3×3 kernels in this system. The effect of using several small convolution kernels is better than using a larger convolution kernel for a given receptive field range because nonlinear layer can increase network depth to ensure more complex patterns are learned, and the computational cost is also lower.

GoogLeNet, which started the same year as VGGNet [35], had similar success. GoogleNet comprises a module called inception in contrast to VGGNet [35]. In order to minimize computation, it has a dense structure of convolutional layers with 1×1 kernel size.

ResNet [40] introduced skip connections, allowing for the training of considerably deeper networks. The network has the option to simply transfer the activations from layer to layer (more specifically, from ResNet block to ResNet block), maintaining information while data moves across the layers, by having skip connections in addition to the usual path. Some features are better extracted in the shallow networks, while others require deeper networks. The simultaneous capability of both is provided via skip connections, enhancing the network's adaptability to input data.

DenseNet [39] was developed on the principles of ResNet, but concatenates the activations produced by one layer with those of later layers rather than adding them. Therefore, each layer (blocks of layers) keeps the original inputs in addition to the activations from previous layers, maintaining some sort of global state. This promotes feature reuse and reduces the number of parameters required for a given depth. Therefore, DenseNets are more suited for smaller datasets.

YOLO [37], introduced a novel, streamlined method for detecting objects in images and classifying them. It employs a single CNN that processes the image directly while outputting bounding boxes and class probabilities. It incorporates a number of components from the aforementioned networks, such as the inception modules and the pretraining smaller network. It moves quickly enough to allow real-time processing. By lowering the size of the model, YOLO makes it simple to exchange accuracy for speed. On a common benchmark data set, YOLOv3-tiny was able to process images at over 200 frames per second while still delivering accurate predictions.

UNet [55] is a well-known and effective network for segmenting 2D images. A traditional CNN is used to downscale an input image before it is upscaled using transpose convolutions till it reaches its original size. Additionally, based on the concepts of ResNet, there are skip connections that combine features from the up-sampling paths and the down sampling paths.

VNet is a three-dimensional version of the U-net with the same skip connections and volumetric convolutions as ResNet.

2.1 Image classification

In the computer-aided diagnosis system, image classification plays an important role. Image classification methods classify input images into classes like fracture or not-fracture or diseases or no-diseases [23, 24]. Normal uses of image classification in clinical applications include glaucoma diagnosis [25], skin disease detection [26, 27], retinopathy-related eye disease detection [28, 29], corneal disease detection [30], Brain cancer [31], and breast cancer [32] detection using pathological images, eye disease [33] detection using OCT, spine fracture classification [34] using CT images. A frequently used classification framework for medical image classification and analysis is the convolutional neural network (CNN) [35]. There is continuous improvement in the CNN framework with the evolution of the deep learning model. The AlexNet [36] was the pioneering CNN architecture, which comprises repeated convolutions with ReLU activation and max pooling. The performance of CNN architecture improved by increasing the depth of architecture in VGGNet [37] with convolution kernels of size 3×3, max pooling with size 2×2, in the inception network [38] with stacking of convolution kernels of sizes 1×1, 3×3, and 5×5 and pooling of size 3×3, and its alternation [39, 40]. Skip connections were used in DenseNet [41] and ResNet [42] to diminish the gradient vanishing. Apart from image classification, the CNN can be used for some other computer applications like segmentation and detection. For the evaluation of binary classification algorithms, commonly used evaluation metrics are recall, precision, accuracy, F1-score, AUC/ROC curve, etc. And for multiclass classification, commonly used evaluation metrics are accuracy and kappa coefficient.

The design of computer-aided decision support systems for fracture detection, lesion detection, cancer detection, and others is an evolving area of research. A computer-aided decision support system in the medical field requires classification of the data. Compared to traditional methods of data augmentation, deep learning-based generative models (GANs) are the best method of augmentation. With a GAN-augmented data set, we can avoid biased results and overfitting of the data. The performance of the CNN classification can be improved with GAN-augmented data.

2.2 Detection of object

Both localization and identification tasks are present in the object detection algorithms. Deciding the classes of the objects that appear in the region of interest is called an identification task, whereas precise localising the object position in the image is termed a localization task. Object detection in medical images aims to detect the abnormality or fracture. Ideal detection tasks in clinical applications comprise using chest X-ray or CT images to detect lung nodules [43, 44], mammogram detection using CT [45], and lesion detection on CT images [46, 47]. Anchor-based methods and anchor-free methods are two different methods in Object detection algorithms. Anchor-based methods are further classified as single-stage and two- or multistage anchor-based methods. Single-stage anchor-based methods are computationally efficient, while on the contrary, the object detection performance of two- or multistage anchor-based methods is better when compared to single-stage anchor-based methods. Widely used single-stage detectors are single-shot multiboxes [48] and the YOLO family [49]. Feed-forward CNN is the basis of multibox and YOLO architectures. A fixed number of bounding boxes are produced by these architectures, and in the boxes, for each object of a given class, architectures produce corresponding scores. Final predictions are obtained by the non-maximum suppression step. The SSD produces better detection performance because it makes use of multiscale feature maps, which is contrary to the YOLO architecture, which makes use of single-scale feature maps. Inference speed is high in a single-stage object detection architecture, whereas in a two-stage architecture, high object recognition and localization performance are present. Faster-RCNN [50] and Mask-RCNN [51] are popular two-stage object detection architectures that generate a set of ROIs. In Faster-RCNN and Mask-RCNN, Region Proposal Networks (RPN) generate bounding boxes in the first stage, and in the second stage, classification is done. The CornerNet [52] is a popular anchor-free technique. It is a single CNN that uses paired key points instead of anchor boxes; the bounding box is defined by the bottom-right and top-left corners. To evaluate the performance of detection methods, two main metrics are used: false positives per image and mean average precision.

2.3 Image segmentation

In deep learning, Image segmentation is a foremost research area. It is a pixel labelling method where images are separated into regions with similar properties. Segmentation techniques determine the outline of a body structure or organ in the medical images. In clinical applications, segmentation is used in segmenting different organs like the liver [53], pancreas [54], and whole heart [55] in CT imaging modalities. Expeditious development in deep learning leads to the development of very good semantic segmentation methods. In image segmentation, Fully Convolutional Neural Network (FCN) [56], which is the first CNN to perform segmentation tasks, has attained great success. In medical image segmentation, there are two categories of image segmentation: 2D and 3D, depending on the dimensions of the input image. For the segmentation of medical images, UNet architecture [57] is extensively used. U-Net comprises a downsample side and an upsample side. For downsampling, it comprises repeated convolutions, which are followed by Rectified Linear Unit (ReLU) and strided max pooling. The number of feature channels is doubled in each step. The upsampling path consists of feature map upsampling, followed by deconvolution with half the number of feature channels. Different types of U-Net-based frameworks have been developed. For the segmentation of the medical images No new U-Net (nnU-Net) is proposed by Isensee et al. [58]. The nnU-Net got excellent performance in segmenting tumours, lesions, and different organs in different imaging modalities across 19 different datasets with 49 segmentations. Polycystic kidneys segmentation [59], segmentation of brain tumours [60], striatum segmentation [61], deformable prostate segmentation [62], segmentation of acute ischemic lesion [63], organs at risk in the neck and head region segmentation using CT images [64], and 3D multiscale FCN segmentation of the spine using MR images [65], kidney by mask R-CNN segmentation [66], liver segmentation [67–71] are some of the medical image segmentation applications. The metrics to evaluate the performance of the segmentation task are Intersection Over Union (IOU) and the dice similarity coefficient method.

2.4 Image restoration

For many years, denoising MR images and estimating noise in MRI have been important research areas [72, 73]. Recently, for denoising medical images, deep learning approaches have been extensively used. Bermudez et al. [74] used deep learning for implicit brain MRI manifold learning. Here, with skip connections, autoencoders are implemented for image denoising. Benou et al. [75] addressed spatiotemporal denoising of brain dynamic contrast-enhanced MR images with bolus injections of contrast agent (CA). The results of quantitative and qualitative denoising were superior to those of spatiotemporal Beltrami, stacked denoising autoencoders [76], and the dynamic Non-Local Means method [77]. Deep learning techniques are also used in filtering the artefacts in spectroscopic MRI [78], automated reference-free detection of patient motion artefacts in MRI [79], and detection and removal of ghosting artefacts in MR spectroscopy [80].

2.5 Image registration

Image fusion or image warping are other names for Image registration. It is the process of overlaying two or more images that are captured from different imaging modalities or different angles. The main aim of medical image registration is to set up optimal correspondence in the images captured by different imaging modalities like CT, X-Ray, MRI, and ultrasound, at different times in longitudinal studies, or from distinct viewpoints like axial, sagittal, and coronal, to collect valuable information. In many medical applications like image-assisted surgery [81], computer-assisted intervention, and treatment planning [82], image registration is a very important pre-processing technique. The overlaying of anatomical images like CT or MRI with functional images like PET scans or functional MRIs is very helpful in disease monitoring and diagnosis [83]. The state-of-the-art performance is achieved by image registration methods that are based on deep learning methods [84]. Abdominal MRI registration was done [85] by applying a CNN to compensate for respiration deformation. Obtaining reliable ground truth is a challenging task in spite of the success of supervised deep learning-based techniques. Unsupervised techniques can effectively diminish the absence of training datasets and ground truth. trained a fully convolutional network to execute deformable brain 3D MRI by self-supervision [86]. Motivated from Spatial Transfer Network (STN) [87], Kuang et al. [88] implemented a CNN based on STN to execute MRI brain volumes deformable registration. Lately, Reinforcement Learning and Generative Adversarial network (GAN)-based techniques have caught attention. 3D ultrasound and MRI registration were performed by Yan et al. [89]. In the implemented work, estimation of the rigid transformation was done by a generator, and a discriminator network was trained to differentiate between ground-truth-based aligned images and predicted ones. The 2D–3D prostate MRI robust nonrigid deformable registration was done by the reinforcement learning method [90]. Retinal imaging, is crucial for diagnosing eye pathologies and systemic disorders. [91–95] presented deep learning approaches are used for registering retinal images. Depending on the imaging modalities, image registration can be categorised into two types: multimodal or monomodal. For evaluation of the performance of image restoration, two of the most commonly used metrics are mean square error and Dice coefficient.

3 Different applications of Generative Adversarial Networks (GANs) in medical image analysis

The Generative Adversarial Networks (GANs) comprises of generator (G) and discriminator (D) networks, where the generator learns input data distribution and uses the noise to generate realistic images. The Discriminator determines whether an image is real or synthetic. Discriminator input data x, the probability distribution is represented as p_{data}. The Generator (G) with θ_g parameters $G(Z, \theta_g)$ map the input noise Z of distribution P_z to data space $P_g(x)$. Similarly, discriminator (D) with parameter θ_d takes real and generated data and gives single scalar probability value as output. GAN plays "minmax" game that is (D) discriminator maximize and (G) generator tries to minimize the chances of predicting the correct classes and is represented by the Eq. (1) [20].

$$G_{min} D_{max} \mathrm{V(G, D)} = E_{x \sim p_{data}}[\ln(D(x))] + E_{z \sim P_z}[\ln(1 - D(G(Z)))] \tag{1}$$

For medical applications, GANs can be applied in two ways. The first is in the generative direction, where it generates a new realistic-looking synthetic image. The second is a discriminator (D) to discriminate images, which can be employed as a detector. The main applications of GANs in medical applications are detection, segmentation, classification, reconstruction, registration, and image synthesis.

Deep Convolutional GAN [96] is proposed in 2015. Both the generator and discriminator in DCGAN use the deep convolutional network and make use of hierarchical feature learning. It consists of a fully connected convolution layer without any max pooling. Batch normalization and the leakyReLU activation function are used in this GAN architecture to enhance training.

Wasserstein-GAN [97] was proposed in 2017. They measure divergence using the Wasserstein distance. It is a GAN extension that uses an alternative training technique for better approximation. Although WGAN is practically quite simple to construct, it has a problem with slow optimisation.

PGGAN [98] can produce realistic images of high quality. The basic process in a PGGAN is to train at a very low resolution, initially starting at 4×4, and then build up the model slowly and iteratively by adding layers and fine-tuning up to exponentially larger resolutions in powers of 2. Prior to being utilised to make the lower resolution images, the input image is centre cropped to reach the proper input resolution. Networks can more easily learn various image styles since they develop adaptively. Instead of having to quickly learn how to map a random noise latent vector to an image with a high resolution, say 512×512 networks gradually pick up this information by starting with a small-scale image, such a 4×4,8×8,16×16, etc., images.

Super-resolution GAN [99] generates higher resolution images, it uses a deep network together with an adversary network. In comparison to a similar design without GAN, SRGAN generates more visually appealing images with more details. Super-resolution (SR) images are upsampled using a GAN generator. The discriminator is used to differentiate between HR images and generated images and backpropagate the GAN loss to train the generator.

Conditional GAN [100] was proposed in the year 2014. Since no explicit control over the data generation is provided in the original GAN, the conditional GAN (cGAN) includes extra information like class labels in the synthesis process. In the cGAN, the generator is given some prior knowledge c along with random noise z. Along with the corresponding real, generated data, the discriminator also receives the prior knowledge c. If a class label is given, it can be used to conditionally generate images of a specific type or class.

For the purpose of transforming images between two domains, the model should be able to extract distinctive features from each domain and identify the underlying relationship between them. The CycleGAN [101] offer these mappings. To identify a mapping from domain X to domain Y and vice versa, the system essentially merges two GANs. A generator G: $X \rightarrow Y$ and a generator F: $Y \rightarrow X$, taught by discriminator D**Y** and discriminator D**X**, respectively, make up these systems. A cyclic loss function causes the two chained GANs to condense the range of potential mapping functions. This cyclic loss function accurately minimises the difference between the original image and the reconstruction produced by the chained generators.

The Pix2Pix is a highly effective cGAN version for high-resolution image-to-image translation. While the discriminator, uses a fully convolutional architecture to distinguish between the real and generated high resolution data, the Pix2Pix [101] generator adheres to the U-Net architecture. The skip connections inside the U-Net generator were advantageous for the overall coherence of the synthesised images. Pix2Pix needs pairs of related input and intended output images, unlike the original GAN framework. This makes it possible to stabilise the training by using the l1 loss between the output of the generators and the actual ground-truth image.

3.1 Image synthesis for data augmentation

In image synthesis, there are two main categories: unconditional image synthesis and cross-modality image synthesis [102]. DCGAN, PGGAN, and WGAN are used for unconditional synthesis, where only the random noise vector is input to the generator and the condition vector is not provided as input. 256×256 resolution images can be generally handled by DCGAN and WGAN, whereas high-resolution images are generated by PGGAN. Table 1 shows unconditional image synthesis work in different imaging modalities. In cross-modality image synthesis, the images of one modality are generated from other modalities (e.g., CT from MRI or vice versa). Pix2Pix GAN and Cycle GAN are extensively used cross-modal image generators. Table 2 shows cross-modality medical image synthesis work in different imaging modalities. And Table 3 shows GAN-based Segmentation in different imaging modalities of medical images.

3.2 Reconstruction

The radiation hazard is the main limitation in medical imaging like MRI, CT, X-rays, etc. To avoid this decrease in radiation dosage, which results in the amplification of noise and affects the diagnostic details in the images [198]. To capture a high-resolution MR image, a large capture time is needed [199], and lower-quality medical images are the result of small-scale graphical coverage. So, reconstruction of the image is needed. The GAN, which generates a realistic-looking image, can be used for reconstruction of images. Table 4 describes some of the reconstruction work done by GAN in medical applications.

Table 1 Unconditional medical image synthesis

Authors	Year	Imaging modality	GAN used	Usage of generated images	Summary
Computed Tomography (CT)					
Maayan et al. [103]	2018	CT	DCGAN	–	Liver lesion are generated by DCGAN
Maayan et al. [104]	2018	CT	DCGAN ACGAN	CNN classification	Classification of liver lesions with augmentation. Compared with other GAN and traditional methods, DCGAN augmented data provides better classifier performance
Takaaki Konishi et al. [105]	2020	CT	DCGAN	–	Realistic liver lesion synthesis using DCGAN
Bowles et al. [106]	2018	CT and MRI	PGGAN	CNN segmentation	With PGGAN, MRI slices and CT images of the brain is generated, resulting in improved segmentation accuracy
Yuya Onishi et al. [107]	2018	CT	WGAN	DCNN classification	Lung cancer pulmonary nodule classification with WGAN generated data
Sindhura et al. [108]	2021	CT	DCGAN	–	Realistic spine fracture CT synthesis using DCGAN
Sindhura et al. [109]	2022	CT	PGGAN	CNN Classification	With PGGAN, CT slices of the spine fracture is generated, resulting in improved classification accuracy
Kang et al. [110]	2021	CT and PET	WGAN-GP	–	Evaluation methods indicate generated brain PET-CT distribution is approximately same as real
Mammographs					
Tianyu Shen et al. [111]	2021	Mammographs	DCGAN	–	Realistic Mammographs synthesis using DCGAN
Korkinof et al. [112]	2018	Mammographs	PGGAN	–	High-resolution realistic mammographs are generated by PGGAN
Magnetic Resonance Imaging (MRI)					
Jonas Denck et al. [113]	2021	MRI	ACGAN	–	Based on Turing test results, MRI generated by ACGAN is realistic
Changhee et al. [114]	2018	MRI	DCGAN WGAN	–	Generating multi-sequence MRIs. WGAN generated more realistic images than DCGAN
Bermudez et al. [115]	2018	MRI	DCGAN	–	Generating more realistic MR images of the brain
Navid G et al. [116]	2019	MRI	DCGAN	CNN classification	Brain tumour classification with DCGAN augmented data
Gab Allah et al. [117]	2021	MRI	PGGAN	VGG19 Classification	MRI of brain generated, increased accuracy of the three class tumors classifier
Ahmad et al. [118]	2022	MRI	VAE + GAN	CNN Classification	Variational autoencoders and GAN augmentation to help with Brain Tumor Classification in MRI
Vashisht et al. [119]	2023	MRI	GAN	CNN Classification	GAN augmentation aided Alzheimer classification
Beers et al. [120]	2018	MRI of brain and Retinopathy Images	PGGAN	–	High resolution Retinopathy Images and MRI of brain are generated

Table 1 (continued)

Authors	Year	Imaging modality	GAN used	Usage of generated images	Summary
Optical Coherence Tomography (OCT)					
Ce Zheng et al. [121]	2021	OCT	PGGAN	–	Good quality of OCT images is generated with PGGAN
X-ray					
Madani et al. [122]	2018	X-Ray	DCGAN	CNN classification	DCGAN generated images increased the performance of classifier than traditional augmentation methods
Hojjat Salehinejad et al. [123]	2019	X-Ray	DCGAN	–	Realistic synthetic chest X-Ray image are generated
Venu et al. [124]	2021	X-Ray	DCGAN	CNN classification	DCGAN generated chest X-Ray images improved the performance of classifier than traditional augmentation method
Bradley Segal et al. [125]	2021	X-Ray	PGGAN	–	Realistic X-rays were generated using PGGAN and evaluated
Others					
Tomoyuki Fujioka et al. [126]	2019	JPEG	DCGAN	–	Generation of breast ultrasound image for cancer detection. DCGAN generated images are more realistic
Zhanyu Wang et al. [127]	2019	JPEG	DGGAN	–	Glaucoma Diagnosis using DCGAN augmented data
Hartanto et al. [128]	2020	JPEG	DCGAN	ResNet50 classifier	White blood cell generated by DCGAN created balanced dataset for classifier
Hui Che et al. [129]	2021	JPEG	DCGAN And Variants of DCGAN	CNN classification	Liver lesions generated by the DCGAN and variants of DCGAN increased the performance of classifier when compare to original dataset classification
Freedom Mutepfe et al. [130]	2021	JPEG	DCGAN	CNN classification	Skin lesions generated increased the binary classification accuracy
Lahiri et al. [131]	2018	Retinal images	DCGAN	Segmentation	Semi supervised DCGAN achieved good performance compared to supervised CNN
Kang Li et al. [132]	2021	Retinal Images	DCGAN Double stage GAN	–	Double stage GAN generated mammographs are more realistic than DCGAN synthetic images
Atsushi Teramot et al. [133]	2020	JPEG	DCGAN PGGAN	DCNN classification	lung cancer cytological imagine classification. 4% improvement in the performance with GAN augmented data
Christoph Baur et al. [134]	2018	JPEG	PGGAN	–	The generation of more realistic skin lesions
Ibrahim Saad Aly Abdelhalim et al. [135]	2021	JPEG	PGGAN	CNN detection	Skin lesions generated by PGGAN increased the performance of detection

3.3 Detection

The supervised deep learning algorithm for anomaly detection in medical images needs a huge annotated or labelled training image. For medical applications, such hugely labelled data is not readily accessible. Depending only on annotated data whose appearance is the same during training limits the ability of supervised DL methods to detect

Table 2 Cross modality image synthesis

Authors	Year	Source→ Result modality	GAN Used	Region of study	Summary of the study
Cycle GAN					
Jiang et al. [136]	2018	CT → MRI	Cycle GAN	UNET Segmentation	CT to MRI generation overcome shortage of MRI in segmentation task
Zizhao Zhang et al. [137]	2018	MRI → CT CT → MRI	Cycle GAN	Heart disease	CT to MRI, MRI to CT translation increase the performance of segmentation
Huo et al. [138]	2018	MRI → CT CT → MRI	Cycle GAN	Spleen	CT to MRI, MRI to CT translation. Effect of translation on the performance of segmentation in SynSeg-Net is evaluated
Hiasa et al. [139]	2018	MRI → CT CT → MRI	Cycle GAN	Musculoskeletal	Translation accuracy is evaluated by segmentation
Pan et al. [140]	2018	MRI→PET	Cycle GAN	Brain	Evaluation implies translated PET is effective in identification of Alzheimer's disease of brain
Bin Jin et al. [141]	2019	CT → MRI	CycleGAN	Brain	Paired and unpaired method of translating CT to MRI done
Kang et al. [142]	2021	CT → MRI	CycleGAN	Abdomen Thorax pelvis	CycleGAN with perceptual loss effectively translated MRI to CT
Peng et al. [143]	2020	CT → MRI	CycleGAN, Conditional GAN	Nasopharyngeal	cGAN generated high-quality CT images from MRI
Tomar et al. [144]	2021	MRI → CT CT → MRI	CycleGAN SASAN	Brain and cardiac	UsgGAN performs better translation in cardiac structure segmentation
Lapaeva et al. [145]	2022	MRI → CT	CycleGAN	Abdominal area	Synthetic CT (sCT) generated from MRI for radiotherapy
Sun et al. [146]	2023	3DMRI → CT	Double U-Net CycleGAN	Brain	Synthetic CT generated from MRI for radiotherapy
pix2pix					
Choi et al. [147]	2017	PET → MRI	pix2pix	Brain	Translated MRI can be used for effective amyloid quantification
Maspero et al. [148]	2018	MRI → CT	Pix2pix	Pelvic region	Translated CT of pelvic region from MRI helps in prostate cancer detection
Conditional GAN					
Yang et al. [149]	2018	MRI → CT CT → MRI	Conditional GAN	Brain	Translated multichannel segmentation of MRI was done in translated images
Emami et al. [150]	2018	MRI → CT	Conditional GAN	Brain	T1 – MRI effectively translated into synthetic CT in less time
Ben-Cohen et al. [151]	2018	CT → PET	FCN + Conditional GAN	Lesion detection	CT to PET generation to improve detection accuracy of liver lesions
Wei et al. [152]	2018	MRI → PET PET → MRI	Cascade cGAN	Brain	Synthetic translated images of brain generated from anatomical feature with the help of sketch-refinement process

Table 2 (continued)

Authors	Year	Source→ Result modality	GAN Used	Region of study	Summary of the study
Ranjan et al. [153]	2022	MRI → CT	Conditional GAN	Brain	Synthetic CT generated from MRI for radiotherapy
Qin et al. [154]	2022	MRI → MRI	Style Transfer Conditional GAN ST-cGAN	Brain	Brain MRI cross-modality synthesis
Others					
Bi et al. [155]	2017	CT → PET	Multichannel GAN	Lung cancer	High resolution PET scan images of lungs generated from the CT scan
Armanious et al. [156]	2020	PET → CT	MedGAN	Brain	Evaluation by radiologist implies good quality CT scan generated by translation
Florkow et al. [157]	2020	MRI → CT	3D U-Net	Pelvic bone	Translated synthetic CT images increased the performance, robustness of DL model
Yanxia Liu et al. [158]	2021	MRI → CT	Multi Cycle GAN	Head and Neck	Designed multicycle GAN performs better translation when compare to traditional GAN
Alaa Abu-Srhan et al. [159]	2021	MRI → CT CT → MRI	usgGAN	Brain	UsgGAN performs better translation when compare to traditional GAN
Yi Gu et al. [160]	2021	CT → MRI	Dual3D and PatchGAN	Multiple domain	Dual3D and PatchGAN performs better translation
Yan et al. [161]	2022	MRI → MRI (Multimodal)	Swin Transformer based GAN (STG)	Brain	Multimodal MRI translation using a STG
Wang et al. [162]	2023	Cross-modality	FedMed-GAN	Brain	cross-modality synthesis of brain images
Jang et al. [163]	2023	MRI → PET Text → PET	TauPETGen	Brain	tau PET synthesis from MRI and text-conditional using latent diffusion models

anomalies. The new paradigm is GAN-based unsupervised anomaly detection. Pioneering work on AnoGAN, implemented in [217], inferred that a similar idea could be helpful in anomaly detection in retinal OCT. Brain anomaly detection in MR images was implemented in [218] and [219]. Similarly, Alzheimer's disease detection using VA-GAN (visual attribution GAN) was implemented [220]. Detection of prostate cancer [221] and skin lesions [228] by GAN, in which the generator uses U-Net and CGAN, respectively. Table 5 summarises how anomaly detection works.

3.4 Registration

Heavy optimisation load and parameter dependency are the drawbacks of traditional registration methods [230]. Medical images are successfully aligned using CNNs in a single forward pass. The Generative Adversarial Networks are considered a candidate to extract optimal registration mapping with their very good image transformation ability. Unsupervised GAN is implemented for structural pattern registration in brain images, where implemented GAN does not require specific similarity metrics or ground truth deformations [231]. An adversarial image registration framework is implemented for the registration of MRI and transrectal ultrasound. This image fusion helps in prostate interventions [232]. In the same way, [233] implemented GANs for deformation regularisation, which helps in training image registration.

3.5 Super-resolution [SR] methods

The generation of high-resolution images from low-resolution images is the main purpose of the SR method. In the GAN-based techniques to improve the resolution of LR images, the patterns are learned in the same region of paired low- and high-resolution training images. In GAN, low-resolution images are given as input to the generator, which generates synthetic SR images as output. And

Table 3 GAN based segmentation in different imaging modalities

Authors	Year	Imaging modality	GAN used	Summary of the study
Computed Tomography (CT)				
Sandfort et al. [164]	2019	CT	Cycle GAN	Segmentation of organs like kidneys, liver, spleen, etc.,
Stiehl et al. [165]	2021	CT	Constrained GAN	Lung lobes segmentation based on quorum method
Jain et al. [166]	2021	CT	GAN	Lung lobes segmentation by GAN based on "Salp Shuffled Shepherd Optimization Algorithm"
Li et al. [167]	2021	CT	GAN	Segmentation of Pancreas
Kan et al. [168]	2021	CT	CFG-SegNet "conditional feature generation segmentation network"	Segmentation of multi organs like uterus, Prostate
Nishiyama et al. [169]	2021	CT	Cycle GAN pix2pix	Gluteus Medius segmentation
Cui et al. [170]	2021	CT MRI	GAN	Cardiac image segmentation by GAN based on bidirectional cross-modality
Conze et al. [171]	2021	CT MRI	Conditional GAN	Segmentation of multi organs like kidneys, liver, spleen, etc.,
Magnetic Resonance Imaging (MRI)				
Xue et al. [172]	2018	MRI	SegAN	SegAN based on Multi-scale L_1 Loss helps in Segmentation of tumor and core of tumor in brain
Rezaei et al. [173]	2018	MRI	Cascade of 3 Conditional GANs	Adversarial networks used in segmenting blood pool and myocardium
Kohl et al. [174]	2018	MRI	Conditional GAN	Improved sensitivity in segmenting prostate
Zhao et al. [175]	2018	MRI	Deep-supGAN "deep-supervision discriminator"	Initial block generates high quality CT image from MRI followed by segmentation of bone in both modalities in next block
Yuan et al. [176]	2019	MRI	Unified Attentional GAN	Translation followed by segmentation helps in segmenting the object in many modalities simultaneously
Nema et al. [177]	2020	MRI	RescueNet "residual cyclic unpaired encoder-decoder "	Segmentation of core tumor, whole tumor region of brain
Xinheng Wu et al. [178]	2021	MRI	Symmetric driven GANs	SD-GAN provided superior performance in segmenting brain tumor compare to state of art unsupervised methods
Cheng et al. [179]	2021	MRI	3D-GAN	Segmentation of core tumor, whole tumor region of brain. By label correction this method is effective in handling false label mask
Wang et al. [180]	2021	MRI	SegDGAN	Segmentation of Prostate gland
Dai et al. [181]	2021	MRI CBCT	Cycle GAN and FPN "Feature pyramid network"	Spine, optic chiasm, left/right cochlea, brain stem, larynx, left/ right eye, oral cavity, mandible, optic chiasm, pharynx, etc. segmentation
Güven et al. [182]	2023	MRI	Supervised SimDCL	Supervised SimDCL, GAN architecture for segmentation of brain MRI
Al Khalil et al. [183]	2023	MRI	GAN	Improving the robustness of DL based segmentation of cardiac MRI with GAN generated data
Al Khalil et al. [184]	2023	MRI	late feature fusion and GAN	Using GAN-based augmentation and late feature fusion to reduce segmentation failures within cardiac MRI
Optical Coherence Tomography (OCT)				
Tennakoon et al. [185]	2018	OCT	GAN	Segmentation of retinal fluid
Ouyang et al. [186]	2019	OCT	Conditional GAN	Segmentation of Cornea and limbus cornea

Table 3 (continued)

Authors	Year	Imaging modality	GAN used	Summary of the study
Schlegl et al. [187]	2019	OCT	f-AnoGAN "Fast unsupervised anomaly detection"	Fundus abnormalities segmentation and detection
Wang et al. [188]	2021	OCT	Cycle GAN	Retinal OCT image anomaly segmentation by weakly supervised method
Others				
Jiang et al. [189]	2018	ICGA	Conditional GAN	Segmentation of Lacquer crack. By using Dice loss function the segmentation accuracy further increased
Son et al. [190]	2019	Funduscopy image	GAN	Fine, thin retinal vessel detection by segmentation using GAN was done
Kadambi et al. [191]	2020	Funduscopy	WGAN	In fundus images WGAN is used to segment optic cup and optic disc
Guo et al. [192]	2020	Mammographs	GAN	Chest muscle segmentation
Yıldız et al. [193]	2021	Microscopy image	GAN Patch GAN	Segmentation of Corneal sub basal nerves
Gilbert et al. [194]	2021	Ultrasound	Cycle GAN	Left atrium and ventricle segmentation by GAN
Brion et al. [195]	2021	CBCT	U-Net GAN	Segmentation of male organs like prostate, rectum, bladder
Kunapinun et al. [196]	2023	Ultrasound	GAN	Enhancing GAN Training Dynamics for Segmenting Thyroid Nodules
Narayanan et al. [197]	2023	Brain Images	U-Net Dual stage GAN	Two-stage GAN, the first stage is DCGAN, which generates a binary tumor mask, and the second stage is the pix2pix GAN network, which applies style transfer and creates a realistic brain image. Followed by U-Net for the segmentation of images

generated images and real SR images are given as input to the discriminator, which distinguishes their authenticity [234]. The Meta-SRGAN implemented [235] generates arbitrary SR images of brain 2D-MRI, which perform well when compared to traditional methods. Meta-SRGAN is a network that uses a Meta-Upscale Module and SRGAN. Rather than a single GAN, [236] implemented an ensemble model for SR-MR knee image synthesis by training multiple GANs and merging multiple outputs into one final output. In terms of peak SNR (peak signal-to-noise ratio) and structural similarity index, the ensemble model performed well. SR methods have been implemented for 3D image generation. A SRGAN-based network with enhanced up-sampling techniques is able to generate realistic synthetic images. The 3D-SRGAN is implemented in [237] to generate high-resolution images from low-resolution MR images of the brain. A multi-scale GAN with patch-wise learning is implemented to generate synthetic high-resolution 2D, 3D CT, and X-Ray thorax images. The GAN suppressed the objects that occur in patch-wise training and generated realistic 3D 512 × 512 thorax CT and 2048 × 2048 thorax X-ray images [238]. High-dose CT images and brain MRIs from low-dose images can also be generated with SRGAN.

3.6 De-noising

In CT and MR images, to reduce the exposure to radiation dose and to decrease image capturing time, Generative Adversarial Networks (GANs) have been implemented to reduce noise in CT and MR images captured in low-dose conditions. De-noising of low-dose single-photon emission computed tomography (SPECT) images was done using GANs [239]. CT images look forward to giving anatomic information; the removal of noise is very important while preserving contrast and the shape of organs. To accomplish this need, GANs that use perceptual sharpness loss The GANs with perceptual loss are implemented to generate high-dose abdominal CT from normal dose and simulated four-dose and are evaluated using a pre-trained VGG [240]. In the other modified type of GAN, a sharpness detection network is added to calculate the denoised image sharpness [241]. The models were trained with high- and low-dose pair CT images, which generate reduced-noise versions of images. Jelmer and team [242] trained the model with low-dose, routine CT pair images to generate synthetic noise-reduced images based on the low-dose images. The GAN-based reduction of noise helps

Table 4 Reconstruction work by GAN in medical applications

Authors	Year	Modality	Purpose of the study	GAN name
Computed Tomography (CT)				
You et al. [200]	2018	CT	From low resolution, counterparts high-resolution CT images are reconstructed	Cycle GAN
Kang et al. [201]	2019	CT	Denoising of multiphase coronary CT images	Cycle GAN
Liu et al. [202]	2020	CT	From noisy projection of the dataset TomoGAN reconstructs CT images	TomoGAN
Zhang et al. [203]	2021	CT	High resolution CT reconstruction from low dose CT	GAN
Dashtbani Moghari et al. [204]	2021	CT	Predicting normal-dose cerebral CT perfusion from low dose using 3D-GAN	3D-GAN
Wang et al. [205]	2023	CT	Utilizing transformer and GAN for CT reconstruction from biplane X-rays	TRCT-GAN
Jiang et al. [206]	2023	CT	CGAN-based transformer for high-quality low-dose SPECT reconstruction	CGAN-based transformer
Rezaei et al. [207]	2023	CT	3D lung tumor reconstruction by GAN	GAN
Ramanathan et al. [208]	2023	CT	Reconstructing Low-Dose CT Images using Vector Quantized Convolutional Autoencoder	Autoencoder
Cone Beam Computerized Tomography (CBCT)				
Liao et al. [209]	2018	CBCT	Sparse view CBCT reconstruction	Cycle GAN
Magnetic Resonance Imaging (MRI)				
Seitzer et al. [210]	2018	MRI	Two stage reconstruction of MRI	GAN
Chen et al. [211]	2018	MRI	3D super-resolution MRI reconstructed from low resolution using mDCSRN "multi-level densely connected super-resolution network"	mDCSRN
Kim et al. [212]	2018	MRI	High resolution MRI of brain generated. And evaluated by classifier	Pix2pix
Mardani et al. [213]	2019	MRI	High quality MRI generated from low dimension folds	LSGAN
Du et al. [214]	2023	MRI	Transformer and GAN based Super-Resolution MRI Reconstruction Network	T-GANs
Positron Emission Tomography (PET)				
Wang et al. [215]	2018	PET	High-quality PET generated from low dose	3D Conditional GAN
Hu et al. [216]	2022	PET	Reconstruction of PET by Residual Swin-Transformer	Residual Swin-Transformer

for accurate quantification of calcification of the coronary artery from low-dose cardiac CT.

4 The datasets and evaluation indicators for various medical applications

Deep learning models have shown remarkable promise in healthcare and other domains, demonstrating that they are capable of performing tasks that humans could. But there are obstacles on the path to success. Large datasets are necessary for the training of deep learning algorithms. Deep learning's applicability to medical image analysis has been limited by the lack of data. The expense of acquiring, annotating, and analysing medical images is high, and ethical restrictions limit their use. This makes it challenging for researchers who are not in the medical field to obtain huge amounts of relevant medical data. Thus, in an attempt to be as thorough as possible, this section of the paper presents a selection of medical imaging datasets for deep learning research (Table 6).

During the classification training process, the evaluation metric is essential to obtaining the best classifier. Therefore, choosing an appropriate assessment metric is crucial to differentiating and achieving the best classifier. The list of commonly used evaluation metrics that are particularly intended for classifier optimization [278] are:

- **Accuracy:** The accuracy metric quantifies the proportion of accurate predictions to all instances examined.
- **Error Rate:** The ratio of inaccurate predictions to the total number of instances evaluated is known as the misclassification error.
- **Sensitivity:** Sensitivity quantifies the percentage of positive patterns that are appropriately classified.
- **Specificity:** Specificity quantifies the percentage of negative patterns that are appropriately classified.

Table 5 Anomaly detection by GAN in medical applications

Authors	Year	Modality	Purpose of the study	GAN Name
(Optical Coherence Tomography) OCT				
Schlegl et al. [217]	2017	OCT	Unsupervised anomaly detection in OCT for marker discovery using DCGAN	DCGAN
Magnetic Resonance Imaging (MRI)				
Chen et al. [218]	2018	MRI	Detection of brain lesion	AnoGAN, WGAN-GP
Baur et al. [219]	2018	MRI	Detection of brain lesion	VAEGAN
Baumgartner et al. [220]	2018	MRI	Alzheimer's disease detection	WGAN
Kohl et al. [221]	2017	MRI	Detection of prostate in MR images	U-Net, GAN
Han et al. [222]	2021	MRI	Detect abnormality in brain at different stages in multisequence MRI	MADGAN "Medical Anomaly Detection GAN"
Reddy et al. [223]	2022	MRI	Detection of Brain tumor in MRI	DCGAN with optimized CNN
Alrashedy et al. [224]	2022	MRI	Detection of Brain tumor in MRI	Vanilla GAN and DCGAN
X-Ray				
Wolleb et al. [225]	2020	X-ray	pleural effusions anomaly detection	DeScarGAN
Nakao et al. [226]	2021	X-Ray	Detection of lesions like bilateral hilar lymphadenopathy, lung mass, pleural effusion, cardiomegaly, dextrocardia	Auto-encoding GAN
Zhao et al. [227]	2021	OCT X-Ray	Abnormality detection	Auto-encoding GAN
Others				
Udrea et al. [228]	2017	Image	Detection of pigmented and non-pigmented skin lesions	GAN, U-net
Tuysuzoglu et al. [229]	2018	Ultrasound image	Detection of skin lesions	GAN

- **Precision:** The positive patterns that are accurately predicted from the total anticipated patterns in a positive class are measured by precision.
- **Recall:** Recall quantifies the percentage of positive patterns that are appropriately classified.
- **F1-score:** The harmonic mean of the recall and precision values is represented by F1 score.
- **Geometric-mean:** This measure is used to maintain a somewhat balanced true positive and true negative rate while optimizing both rates.
- **Averaged Accuracy, Averaged Error Rate:** Average accuracy and error of all classes.
- **Averaged Precision, Averaged Recall, Averaged F1-Measure:** Average of per-class precision, Recall, F1-score.

Artificial intelligence research has grown rapidly over the past years due to deep learning models, particularly in the area of medical image segmentation. The list of commonly used evaluation metrics for segmentation [279] are: DSC: Dice Similarity Coefficient, IoU: Intersection-over-Union, Sensitivity, Specificity, Accuracy, ROC: Receiver Operating Characteristic, AUC: Area Under the ROC curve, Cohen's Kappa (Kap), AHD: Average Hausdorff Distance.

5 Discussion

The main purpose of this work is to review deep learning model applications in Classification, segmentation, detection, restoration, registration, and GAN applications like data augmentation, segmentation, reconstruction, detection, denoising, and registration of medical images.

Deep learning models are most widely used for medical image classification and segmentation, and many works have been published in this area. For example, breast lesion segmentation and classification by an automated CNN approach were successfully implemented in [280]. Similarly, Segmentation of Cone-Beam CT for Oral Lesion Detection by the DL model was implemented in [281]. In classification applications, DL models based on CNN have seen progress. In medical image classification, CNN's success led the researchers to explore its benefits in classification. For instance, CNN's automatic classification of anatomical location and medical image modality got very good results [282]. Similarly, the lung nodule classification using the DL model [283], breast cancer classification [284], MRI brain tumour classification [285], shoulder fracture detection [286], COVID-19 detection [287], and cardiomyopathies classification in MRI [288]

Table 6 Dataset for medical applications

Dataset	year	Organ/modality	Employed In		
			Segmentation	Classification	Others
AutoImplant [243]	2020	Brain/MRI	–	–	Cranioplasty Generation
AccelMR [244]	2020	Brain/MRI	–	–	Generation
MRI WM Reconstruction [245]	2020	Brain/MRI	–	–	Generation
Calgary Campinas Brain Dataset [246]	2020	Brain/MRI	–	–	Generation
CT-ICH [247]	2020	Brain/CT	Intracranial hemorrhage	–	
BraTS 2020 [248–250]	2020	Brain/MRI	Brain tumor	–	
FastMRI [251]	2018	Brain/MRI	–	–	Generation
CADA-AS	2020	Brain/MR Angiography	Brain tumor	–	
CADA-RRE	2020	Brain/MR Angiography	Brain tumor	–	
CADA	2020	Brain/MR Angiography	Brain tumor	–	
RIADD[252]	2020	Eye/Fundus photograph	–	Eye-disease classification	
The 2nd Deep DRiD	2020	Eye/Fundus photograph	–	Eye-disease classification	
REFUGE 2 [253]	2020	Eye/Fundus photograph	Yes	Eye-disease classification	Detection
AGE [254]	2019	Eye/OCT	–	Eye-disease classification	Detection
Retinal OCT Images [255, 256]	2018	Eye/OCT	–	Eye-disease classification	–
MICCAI 2020: HECKTOR	2020	Head and neck/ CT and PT	Head and neck tumor	–	–
TN-SCUI 2020 [257]	2020	Head and neck/ Ultrasound	–	–	Detection
Head Neck Radiomics HN1 [258, 259]	2019	Head and neck/ CT	Head and neck squamous cell carcinoma	–	–
MNMS Challenge [260]	2020	Chest and abdomen /MRI	Heart Segmentation	–	–
Automated Segmentation of Coronary Arteries	2020	Chest and abdomen /CT	yes	–	–
C4KC-KiTS [261, 262]	2019	Chest and abdomen /CT	Kidney Segmentation	–	–
MS-CMRSeg 2019 [263, 264]	2019	Chest and abdomen /MRI	Heart Segmentation	–	–
CAMUS [265]	2019	Chest and abdomen/ Ultrasound	Heart Segmentation	–	–
CT-ORG [266–268]	2019	Chest and abdomen/ CT	Lung Liver Kidney Segmentation	–	–
CT Diagnosis of COVID-19 [269]	2020	Chest and abdomen/ CT	–	COVID–19 classification	–
Covid19 Challenge.eu	2020	Chest and abdomen/ CT	–	COVID–19 classification	–
Object CXR	2020	Chest and abdomen/ CT	–	COVID–19 classification	Detection
CORD-19 [270]	2020	Chest and abdomen/ CT	–	COVID–19 classification	–
COVID-Net [271]	2020	Chest and abdomen/ Ultrasound	–	COVID–19 classification	–
COVID-19 CT Segmentation Dataset	2020	Chest and abdomen/ CT	yes	–	–
COVID-19 Lung CT Lesion Segmentation Challenge 2020	2020	Chest and abdomen/ CT	yes	–	–
BCS-DBT [272, 273]	2020	Chest and abdomen/ Digital breast tomosynthesis	–	Breast cancer classification	Detection

Table 6 (continued)

Dataset	year	Organ/modality	Employed In		
			Segmentation	Classification	Others
Lung-PET-CT-Dx [274]	2020	Chest and abdomen/ CT and PT	–	Lung cancer classification	–
LNDb Challenge	2020	Chest and abdomen/ CT	–	Pulmonary nodule classification	Detection
A-AFMA-Detection	2020	Chest and abdomen/ Ultrasound	–	–	Detection of Amniotic fluid detection
KNOAP2020	2020	Bone/ MRI and X-Ray	–	Classification of Knee osteoarthritis	–
MICCAI 2020 RibFrac Challenge [275]	2020	Bone/CT	–	Classification of rib fracture	Detection of rib fracture
Spinal Cord MRI Public Database	2020	Bone/MRI	yes	–	–
VerSe 20	2020	Bone/CT	Vertebra Segmentation	–	–
EVerSe 19 [276, 277]	2019	Bone/CT	Vertebra Segmentation	–	–

have also been implemented successfully. The remaining applications of the DL model in the medical field relating to detection, restoration, and registration are also evolving areas in medical applications.

Lately, the number of medical applications implementing GANs has increased remarkably. A major portion of GAN's works are medical image synthesis in its own modality and cross modality, indicating image synthesis is the most important GAN usage in medical applications. The literature shows that among all imaging modalities, MR images are ranked as the most popular imaging modality explored by GANs. MRI acquisition requires a large amount of time, which may be the main reason for the remarkable interest in using GANs for MRI. GANs generate synthetic MRI sequences from acquired images, which reduces image acquisition time. Other popular medical applications of GAN include segmentation and reconstruction frameworks. On generator output, strong texture and shape regulations are imposed, which results in promising performance of both tasks. For instance, adversarial loss improves 3D CT liver segmentation performance on non-contrast CT better than CRF and graph cut [289]. Further, the applications that utilised GAN for augmenting the data in classification focused more on generating synthetic objects like fractures, lesions, nodules, cells, etc. The training of a neural network (CNN) relies on a large data set to improve the generalisation of the network and reduce overfitting. Traditional data augmentation techniques like rotation, flipping, colour jittering, etc. are not as effective as data augmentation by GAN, which may be because of the smaller distribution variation in the synthetically generated images compared to real ones. For example, implementations that use GAN for generating chest X-rays [290] are used in the detection of pneumonia and COVID-19. The remaining applications of GAN in the medical field relating to registration, reconstruction, detection, denoising, and SR are so limited that it is difficult to draw any conclusions.

6 Conclusion

The main requirement for the clinically assisted decision support system for medical image analysis is the need of the hour. This paper contains the details and strategies of Deep Learning and Generative Adversarial Networks for medical image analysis in CADs. There are two main objectives. The first objective is a deep learning model for medical image analysis. The second objective is generative adversarial networks in medical image analysis. The successful DL models were reviewed in different medical image applications, like Classification, segmentation, detection, restoration, and registration. The DL-based models got good results in classification, segmentation, and detection and are used most commonly in medical image applications. For medical challenges Various solutions exist. Although there are still some issues in medical image applications that are required to be addressed with DL models, Numerous current DL model implementations, including supervised, semi-supervised, and unsupervised models, are slowly developing that can manage real data without manual labelling. The DL model aims to help radiologists make clinical decisions. Automation of radiologist workflow can be done by the DL model to ease decision-making among radiologists. The DL model is also able to aid physicians by automatically classifying and identifying lesions, minimising medical errors, and minimising time for interpretation. In the next few decades, DL-based CADs utilising medical images will be widely used for patient care. Hence, scientists, radiologists, and physicians look for ways to provide good patient care with the aid of DL models. Due to the limited availability of labelled data sets, weakly supervised and unsupervised techniques are emerging areas of research in DL-based medical image analysis. Similarly, different Generative Adversarial Network (GAN) architectures were implemented as powerful tools for medical imaging applications. GANs have realised data augmentation, segmentation, reconstruction, detection, denoising, and registration of medical images. The achievement of short-time image acquisition, low-dose imaging, and maintained quality of images were marked as clinically important features. Domain adaptation that uses available expertise is required to be a quick solution with less time for emerging issues. Further advancement in network models and computational power will permit new applications to deal with higher-dimensional images, like temporal and volumetric imaging. Overall, deep learning and generative adversarial networks are novel, fast-developing fields in medical image analysis that offer many obstacles, opportunities, and solutions.

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References

1. Puttagunta, M., Ravi, S.: Medical image analysis based on deep learning approach. Multimed. Tools. Appl. **80**(16), 24365–24398 (2021). https://doi.org/10.1007/s11042-021-10707-4
2. Liu, W., Wang, Z., Liu, X., Zeng, N., Liu, Y., Alsaadi, F.E.: A survey of deep neural network architectures and their applications. Neurocomputing **234**, 11–26 (2017). https://doi.org/10.1016/j.neucom.2016.12.038
3. Mazurowski, M.A., Buda, M., Saha, A., Bashir, M.R.: Deep learning in radiology: an overview of the concepts and a survey of the state of the art with a focus on MRI. J. Magn. Reson. Imaging **49**(4), 939–954 (2019). https://doi.org/10.1002/jmri.26534
4. Bauer, S., Wiest, R., Nolte, L.P., Reyes, M.: A survey of MRI-based medical image analysis for Brain Tumor studies. Phys. Med. Biol. **58**(13), 1–44 (2013). https://doi.org/10.1088/0031-9155/58/13/R97
5. Valliani, A.A.A., Ranti, D., Oermann, E.K.: Deep learning and neurology: a systematic review. Neurol Ther **8**(2), 351–365 (2019). https://doi.org/10.1007/s40120-019-00153-8
6. Bizopoulos, P., Koutsouris, D.: Deep learning in cardiology. IEEE Rev. Biomed. Eng. **12**(c), 168–193 (2019). https://doi.org/10.1109/RBME.2018.2885714
7. Dhillon, A., Verma, G.K.: Convolutional Neural Network: a review of models, methodologies, and applications to object detection. Progress Artif. Intell. (2019). https://doi.org/10.1007/s13748-019-00203-0.30
8. Dimitriou, N., Arandjelović, O., Caie, P.D.: Deep learning for whole slide image analysis: an overview. Front. Med. **6**(November), 1–7 (2019). https://doi.org/10.3389/fmed.2019.00264
9. Du, W., et al.: Review on the applications of deep learning in the analysis of gastrointestinal endoscopy images. IEEE Access **7**, 142053–142069 (2019). https://doi.org/10.1109/ACCESS.2019.2944676
10. Dugas, C., Bengio, Y., Bélisle, F., Nadeau, C., Garcia, R.: Incorporating second-order functional knowledge for better option pricing. In: 13th International Conference on Neural Information Processing Systems (NIPS'00), pp. 451–457 (2000). https://doi.org/10.5555/3008751.3008817.
11. Eberhart, R.C., Dobbins, R.W.: Early neural network development history: the age of Camelot. IEEE Eng. Med. Biol. Mag. **9**(3), 15–18 (1990). https://doi.org/10.1109/51.59207
12. Falk, T., Mai, D., Bensch, R., Çiçek, O., Abdulkadir, A., Marrakchi, Y., et al.: U-Net: deep learning for cell counting, detection, and Morphometry. Nat. Methods **16**(1), 67–70 (2019). https://doi.org/10.1038/s41592-018-0261-2
13. Fan, D.-P., et al.: Inf-Net: Automatic COVID-19 Lung Infection Segmentation from CT scans, pp. 1– 10, (2020). Available: http://arxiv.org/abs/2004.14133.
14. Fischer, A., Igel, C.: Training restricted Boltzmann machines: an introduction. Pattern Recogn. **47**, 25–39 (2014). https://doi.org/10.1016/j.patcog.2013.05.025
15. Fonseca, P., Mendoza, J., Wainer, J., Ferrer, J., Pinto, J.A., Guerrero, J., Castañeda, B.: Automatic breast density classification using a Convolutional Neural Network architecture search procedure. Med. Imaging Comput. Diagnosis **9414**(c), 941428 (2015). https://doi.org/10.1117/12.2081576
16. Fukushima, K.: Neocognitron: a self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. Biol. Cybern. **36**(4), 193–202 (1980). https://doi.org/10.1007/BF00344251

17. Gadermayr, M., Gupta, L., Appel, V., Boor, P., Klinkhammer, B.M., Merhof, D.: Generative adversarial networks for facilitating stain-independent supervised and unsupervised segmentation: a study on kidney histology. IEEE Trans. Med. Imaging **38**(10), 2293–2302 (2019). https://doi.org/10.1109/TMI.2019.2899364
18. Gardezi, S.J.S., Elazab, A., Lei, B., Wang, T.: Breast cancer detection and diagnosis using mammographic data: systematic review. J. Med. Internet Res. **21**(7), 1–22 (2019). https://doi.org/10.2196/14464
19. Geras, K.J., et al.: High-Resolution Breast Cancer Screening with Multi-View Deep Convolutional Neural Networks, pp. 1–9 (2017). Available: http://arxiv.org/abs/1703.07047.
20. Goodfellow, I., Bengio, Y., Courville, A.: Deep learning. Nat. Methods (2016). https://doi.org/10.1038/nmeth.3707
21. Goodfellow, I.J., et al.: Generative adversarial nets. Adv. Neural. Inf. Process. Syst. **3**(January), 2672–2680 (2014)
22. Greenspan, H., Van Ginneken, B., Summers, R.M.: Guest editorial deep learning in medical imaging: overview and future promise of an exciting new technique. IEEE Trans. Med. Imaging **35**(5), 1153–1159 (2016). https://doi.org/10.1109/TMI.2016.2553401
23. Yadav, S., Jadhav, S.: Deep convolutional neural network based medical image classification for disease diagnosis. J. Big Data **6**(1), 113 (2019)
24. Wang, C., Zhang, F., Yu, Y., Wang, Y.: BR-GAN: Bilateral Residual Generating Adversarial Network for Mammogram Classification. https://doi.org/10.1007/978-3-030-59713-9_63.
25. Bai, X., Niwas, S.I., Lin, W., et al.: Learning ECOC code matrix for multiclass classification with application to glaucoma diagnosis. J. Med. Syst. **40**(4), 1–10 (2016)
26. Esteva, A., Kuprel, B., Novoa, R.A., et al.: Dermatologist-level classification of skin cancer with deep neural networks. Nature **542**(7639), 115–118 (2017)
27. Wu, H., Yin, H., Chen, H., et al.: A deep learning, Image based approach for automated diagnosis for inflammatory skin diseases. Ann. Transl. Med. **8**(9), 581 (2020)
28. Ting, D.S.W., Cheung, C.Y.L., Lim, G., et al.: Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA **318**(22), 2211–2223 (2017)
29. Gulshan, V., Peng, L., Coram, M., et al.: Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA **316**(22), 2402–2410 (2016)
30. Gu, H., Guo, Y., Gu, L., et al.: Deep learning for identifying corneal diseases from ocular surface slit-lamp photographs. Sci. Rep. **10**(1), 17851 (2020)
31. Ker, J., Bai, Y., Lee, H.Y., Rao, J., Wang, L.: Automated brain histology classification using machine learning. J. Clin. Neurosci. **66**, 239–245 (2019)
32. Spanhol, F.A., Oliveira, L. S., Cavalin, P. R., Petitjean, C., and Heutte, L.: Deep features for breast cancer histopathological image classification. In 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 1868–1873 (2017)
33. Hassan, E., Elmougy, S., Ibraheem, M.R., Hossain, M.S., AlMutib, K., Ghoneim, A., et al.: Enhanced deep learning model for classification of retinal optical coherence tomography images. Sensors **23**(12), 5393 (2023)
34. Sindhura, D.N., Pai, R.M., Bhat, S.N., Manohara-Pai, M.M.: Deep learning-based automated spine fracture type identification with clinically validated GAN generated CT images. Cogent Eng. **11**(1), 2295645 (2024)
35. Ciresan, D., Meier, U., and Schmidhuber, J.: Multi-column deep neural networks for image classification. In: IEEE Conference on Computer Vision and Pattern Recognition, pp. 3642–3649, Providence, RI, USA (2012)
36. Krizhevsky, A., Sutskever, I., Hinton, G.E.: ImageNet classification with deep convolutional neural networks. Commun. ACM **60**(6), 84–90 (2017)
37. Simonyan, K., and Zisserman, A.: Very Deep Convolutional networks for large-scale image recognition. Computer, International Conference on Learning Representations, San Diego, CA, USA (2014)
38. Szegedy, C., Liu, W., Jia, Y., et al.: Going deeper with convolutions. In: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1–9, Boston, MA, USA (2015)
39. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. and Wojna, Z.: Rethinking the inception architecture for computer vision. (2015). https://arxiv.org/abs/1512.00567
40. Szegedy, C., Ioffe, S., Vanhoucke, V., and Alemi, A.: Inceptionv4, inception-resnet and the impact of residual connections on learning. (2016). https://arxiv.org/abs/1602.07261
41. Huang, G., Liu, Z., Van Der Maaten, L., and Weinberger, K. Q.: Densely connected convolutional networks. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA (2017)
42. He, K., Zhang, X., Ren, S., and Sun, J.: Deep residual learning for image recognition. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA (2016)
43. Lo, S.B., Lou, S.A., Lin, J.S., Freedman, M.T., Chien, M.V., Mun, S.K.: Artificial Convolution Neural Network techniques and applications for lung nodule detection. IEEE Trans. Med. Imaging **14**(4), 711–718 (1995). https://doi.org/10.1109/42.476112
44. Liu, J., Zhao, G., Yu, F., Zhang, M., Wang, Y., and Yizhou, Y.: Align, attend and locate: chest x-ray diagnosis via contrast induced attention network with limited supervision. In: 2019 IEEE/CVF International Conference on Computer Vision (ICCV), pp. 10632–10641, Seoul, Korea (2019)
45. Liu, Y., Zhang, F., Zhang, Q., Wang, S., Wang, Y., and Yizhou, Y.: Cross-view correspondence reasoning based on bipartite graph convolutional network for mammogram mass detection. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, USA (2020)
46. Li, Z., Zhang, S., Zhang, J., Huang, K., Wang, Y., and Yizhou, Y.: MVP Net: multi-view FPN with position-aware attention for deep universal lesion detection. In: D. Shen, Ed. Medical Image Computing and Computer Assisted Intervention – MICCAI. MICCAI 2019, vol. **11769** of Lecture Notes in Computer Science, Springer, Cham (2019)
47. Zhang, S., Xu, J., Chen, Y.-C. et al.: Revisiting 3D context modeling with supervised pre-training for universal lesion detection in CT slices. In: Medical Image Computing and Computer Assisted Intervention – MICCAI 2020, A. L. Martel, Ed., vol. **12264** of Lecture Notes in Computer Science, Springer, Cham (2020)
48. Liu, W. et al.: SSD: Single Shot MultiBox Detector. In: Leibe, B., Matas, J., Sebe, N., Welling, M. (eds) Computer vision – ECCV 2016. ECCV 2016. Lecture Notes in Computer Science (), vol. **9905**. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-46448-0_2
49. Redmon, J., Divvala, S., Girshick, R., and Farhadi, A.: You only look once: unified, real-time object detection. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 779–788 (2016)
50. Ren, S., He, K., Girshick, R., Sun, J.: Faster R-CNN: towards real-time Object detection with region proposal networks. IEEE Trans. Pattern Anal. Mach. Intell. **39**(6), 1137–1149 (2017)

51. Gkioxari, G., Dollar, P., and Girshick, R.: Mask R-CNN. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 2961–2969 (2017)
52. Law, H., & Deng, J.: Cornernet: Detecting objects as paired keypoints. In: Ferrari, V., Sminchisescu, C., Weiss, Y., & Hebert, M. (Eds.) Computer Vision – ECCV 2018—15th European Conference, 2018, Proceedings (pp. 765–781), Vol. **11218** LNCS. Springer Verlag (2018). https://doi.org/10.1007/978-3-030-01264-9_45
53. Li, X., Chen, H., Qi, X., Dou, Q., Fu, C.W., Heng, P.A.: H-DenseUNet: hybrid densely connected UNet for liver and tumor segmentation from CT volumes. IEEE Trans. Med. Imaging **37**(12), 2663–2674 (2018)
54. Fang, C., Li, G., Pan, C., Li, Y., and Yizhou, Y.: Globally guided progressive fusion network for 3D pancreas segmentation. In: Shen, D. (ed.) Medical Image Computing and Computer Assisted Health Data Science 11 Intervention – MICCAI 2019, vol. **11765** of Lecture Notes in Computer Science, Springer, Cham (2019)
55. Ye, C., Wang, W., Zhang, S., Wang, K.: multi-depth fusion network for whole-heart CT image segmentation. IEEE Access **7**, 23421–23429 (2019)
56. Long, J., Shelhamer, E., Darrell, T.: Fully convolutional networks for semantic segmentation. IEEE Trans. Pattern Anal. Mach. Intel. **39**(4), 640–651 (2014)
57. Ronneberger, O., Fischer, P., and Brox, T.: U-Net: Convolutional networks for biomedical image segmentation. In: Navab, N., Hornegger, J., Wells, W., and Frangi, A. (Eds.) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015, vol. **9351** of Lecture Notes in Computer Science, Springer, Cham (2015)
58. Isensee, F., Jaeger, P. F., Kohl, S. A. A., Petersen, J., and Maier-Hein, K. H.: Automated design of deep learning methods for biomedical image segmentation. https://arxiv.org/abs/1904.08128.
59. Kline, T.L., Korfiatis, P., Edwards, M.E., Blais, J.D., Czerwiec, F.S., Harris, P.C., et al.: Performance of an Artificial Multi-observer Deep neural network for fully automated segmentation of polycystic kidneys. J. Digit. Imaging **30**, 442–448 (2017)
60. Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., et al.: Brain tumour segmentation with deep neural networks. Med. Image Anal. **35**, 18–31 (2017)
61. Choi, H., Jin, K.H.: Fast and robust segmentation of the striatum using deep convolutional neural networks. J. Neurosci. Methods **274**, 146–153 (2016)
62. Guo, Y., Gao, Y., Shen, D.: Deformable MR prostate segmentation via deep feature learning and sparse patch matching. IEEE Trans. Med. Imaging **35**, 1077–1089 (2016)
63. Chen, L., Bentley, P., Rueckert, D.: Fully automatic acute ischemic lesion segmentation in DWI using convolutional neural networks. NeuroImage Clin. **15**, 633–643 (2017)
64. Ibragimov, B., Xing, L.: Segmentation of organs-at-risks in head and neck CT images using convolutional neural networks. Med. Phys. **44**, 547–557 (2017)
65. Li, X., Dou, Q., Chen, H., Fu, C.-W., Qi, X., Belav, D.L., et al.: 3D multi-scale FCN with random modality voxel dropout learning for intervertebral disc localization and segmentation from multi-modality MR images. Med. Image Anal. **45**, 41–54 (2018)
66. Goyal, M., Guo, J., Hinojosa, L., Hulsey, K., & Pedrosa, I.: Automated kidney segmentation by mask R-CNN in T2-weighted magnetic resonance imaging. In: Medical Imaging 2022: Computer-Aided Diagnosis (Vol. **12033**, pp. 803–808). SPIE (2022)
67. Kushnure, D.T., Tyagi, S., Talbar, S.N.: LiM-Net: lightweight multi-level multiscale network with deep residual learning for automatic liver segmentation in CT images. Biomed. Signal Process. Control **80**, 104305 (2023)
68. Ashtari, P., Sima, D.M., De Lathauwer, L., Sappey-Marinier, D., Maes, F., Van Huffel, S.: Factorizer: a scalable interpretable approach to context modeling for medical image segmentation. Med. Image Anal. **84**, 102706 (2023)
69. Yuan, F., Zhang, Z., Fang, Z.: An effective CNN and transformer complementary network for medical image segmentation. Pattern Recogn. **136**, 109228 (2023)
70. Wu, Y., Liao, K., Chen, J., Wang, J., Chen, D.Z., Gao, H., Wu, J.: D-former: a u-shaped dilated transformer for 3d medical image segmentation. Neural Comput. Appl. **35**(2), 1931–1944 (2023)
71. Chaitanya, K., Erdil, E., Karani, N., Konukoglu, E.: Local contrastive loss with pseudo-label based self-training for semi-supervised medical image segmentation. Med. Image Anal. **87**, 102792 (2023)
72. Sijbers, J., den Dekker, A.J., Van Audekerke, J., Verhoye, M., Van Dyck, D.: Estimation of the noise in magnitude MR images. Magn. Reson. Imaging **16**, 87–90 (1998)
73. McVeigh, E.R., Henkelman, R.M., Bronskill, M.J.: Noise and filtration in Magnetic Resonance Imaging. Med. Phys. **12**, 586–591 (1985)
74. Bermudez, C., Plassard, A.J., Davis, T.L., Newton, A.T., Resnick, S.M., Landman, B.A.: Learning implicit brain MRI manifolds with deep learning. Proc SPIE;10574 (2018)
75. Benou, A., Veksler, R., Friedman, A., Riklin, R.T.: Ensemble of expert Deep neural networks for spatiotemporal denoising of contrast enhanced MRI sequences. Med. Image Anal. **42**, 145–159 (2017)
76. Vincent, P., Larochelle, H., Lajoie, I., Bengio, Y., Manzagol, P.-A.: Stacked denoising autoencoders: learning useful representations in a Deep network with a local denoising criterion. J. Mach. Learn. Res. (JMLR) **11**, 3371–3408 (2010)
77. Gal, Y., Mehnert, A.J.H., Bradley, A.P., McMahon, K., Kennedy, D., Crozier, S.: Denoising of dynamic contrast-enhanced MR images using dynamic non-local means. IEEE Trans. Med. Imaging **29**, 302–310 (2010)
78. Gurbani, S.S., Schreibmann, E., Maudsley, A.A., Cordova, J.S., Soher, B.J., Poptani, H., et al.: A convolutional neural network to filter artifacts in spectroscopic MRI. Magn. Reson. Med. **80**, 1765–1775 (2018)
79. Kustner, T., Liebgott, A., Mauch, L., Martirosian, P., Bamberg, F., Nikolaou, K., et al.: Automated reference-free detection of motion artifacts in magnetic resonance images. MAGMA **31**, 243–256 (2018)
80. Kyathanahally, S.P., Dring, A., Kreis, R.: Deep learning approaches for detection and removal of ghosting artifacts in MR spectroscopy. Magn. Reson. Med. **80**, 851–863 (2018)
81. Miller, K., Wittek, A., Joldes, G., et al.: Modelling brain deformations for computer-integrated neurosurgery. Int. J. Num. Methods Biomed. Eng. **26**(1), 117–138 (2010)
82. Staring, M., van der Heide, U.A., Klein, S., Viergever, M.A., Pluim, J.: Registration of cervical MRI using multifeature mutual information. IEEE Trans. Med. Imaging **28**(9), 1412–1421 (2009)
83. Huang, X., Jing Ren, G., Guiraudon, D.B., Peters, T.M.: Rapid dynamic image registration of the beating heart for diagnosis and surgical navigation. IEEE Trans. Med. Imaging **28**(11), 1802–1814 (2009)
84. Haskins, G., Kruger, U., Yan, P.: Deep learning in medical image registration: a survey. Mach. Vis. Appl. **31**, 1–2 (2020)
85. Lv, J., Yang, M., Zhang, J., Wang, X.: Respiratory motion correction for free-breathing 3D abdominal MRI using CNN-based image registration: a feasibility study. Br. J. Radiol. **91**, 20170788 (2018)

86. Li, H., and Fan, Y.: Non-rigid image registration using self-supervised fully convolutional networks without training data. In: 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), pp. 1075–1078, Washington, DC, USA (2018)
87. Jaderberg, M., Simonyan, K., Zisserman, A., Kavukcuoglu, K.: Spatial transfer networks. Adv. Neural. Inf. Process. Syst. **28**, 2017–2025 (2015)
88. Kuang, D., and Schmah, T.: FAIM-a ConvNet method for unsupervised 3D medical image registration. (2018). https://arxiv.org/abs/1811.09243
89. Yan, P., Xu, S., Rastinehad, A. R., and Wood, B. J.: Adversarial image registration with application for MR and TRUS image fusion. (2018). https://arxiv.org/abs/1804.11024
90. Kreb, J., Mansi, T., Delingette, H., et al.: Robust non-rigid registration through agent-based action learning. In: Medical Image Computing and Computer Assisted Intervention – MICCAI 2017. (2017)
91. Rivas-Villar, D., Hervella, Á.S., Rouco, J., Novo, J.: Color fundus image registration using a learning-based domain-specific landmark detection methodology. Comput. Biol. Med. **140**, 105101 (2022)
92. Sindel, A., Hohberger, B., Maier, A., & Christlein, V.: Multi-modal retinal image registration using a keypoint-based vessel structure aligning network. In: International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 108–118). Cham: Springer Nature Switzerland (2022)
93. An, C., Wang, Y., Zhang, J., Nguyen, T.Q.: Self-supervised rigid registration for multimodal retinal images. IEEE Trans. Image Process. **31**, 5733–5747 (2022)
94. Zhou, J., Jin, K., Gu, R., Yan, Y., Zhang, Y., Sun, Y., Ye, J.: Color fundus photograph registration based on feature and intensity for longitudinal evaluation of diabetic retinopathy progression. Front. Phys. **10**, 978392 (2022)
95. Rivas-Villar, D., Hervella, Á.S., Rouco, J., Novo, J.: Joint keypoint detection and description network for color fundus image registration. Quant. Imaging Med. Surg. **13**(7), 4540 (2023)
96. Radford, A., Metz, L., Chintala, S.: Unsupervised representation learning with deep convolutional generative adversarial networks. (2015). http://arxiv.org/1511.06434
97. Arjovsky, M., Chintala, S., Bottou, L.: Wasserstein generative adversarial net- works. In: International conference on machine learning. (2017). http://arxiv.org/1510.07818v1
98. Karras, T., Aila, T., Laine, S., Lehtinen, J.: Progressive growing of GANs for improved quality, stability, and variation. (2017). http://arxiv.org/1710.10196
99. Ledig, C., Theis, L., Huszar, F., et al.: Photo-realistic single image super-resolution using a generative adversarial network. In: IEEE Conference on Computer Vision and Pattern Recognition, 105–114 (2017)
100. Mirza, M., Osindero, S.: Conditional generative adversarial nets. (2014). http://arxiv.org/1411.1784
101. Isola, P., Zhu, J.-Y., Zhou, T., Efros, A.A.: Image-to-image translation with conditional adversarial networks. (2016). http://arxiv.org/1611.07004
102. Yi, X., Walia, E., Babyn, P.: Generative adversarial network in medical imaging: A review. Med. Image Anal. **58**, 101552 (2019)
103. Frid-Adar, M., Klang, E., Amitai, M., Goldberger, J., and Greenspan, H.: Synthetic data augmentation using GAN for improved liver lesion classification. In: Proceeding of - International Symposium of Biomedicene Imaging, vol. 2018-April, no. Isbi, pp. 289–293 (2018). https://doi.org/10.1109/ISBI.2018.8363576
104. Frid-Adar, M., Diamant, I., Klang, E., Amitai, M., Goldberger, J., Greenspan, H.: GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification. Neurocomputing **321**, 321–331 (2018). https://doi.org/10.1016/j.neucom.2018.09.013
105. Urakawa, T., Tanaka, Y., Goto, S., Matsuzawa, H., Watanabe, K., Endo, N.: Detecting intertrochanteric hip fractures with orthopedist-level accuracy using a deep convolutional neural network. Skeletal Radiol. **48**(2), 239–244 (2019). https://doi.org/10.1007/s00256-018-3016-3
106. Bowles, C., Chen, L., Guerrero, R., Bentley, P., Gunn, R., Hammers, A., Dickie, D.A., Hernández, M.V., Wardlaw, J., Rueckert, D.: GAN augmentation: augment- ing training data using generative adversarial networks. (2018). http://arxiv.org/abs/1810.10863
107. Onishi, Y., et al.: Automated pulmonary nodule classification in computed tomography images using a deep convolutional neural network trained by generative adversarial networks. Biomed. Res. Int. (2019). https://doi.org/10.1155/2019/6051939
108. Sindhura, D. N., Pai, R. M., Bhat, S. N., & MM, M. P.: Synthetic Vertebral Column Fracture Image Generation by Deep Convolution Generative Adversarial Networks. In 2021 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT) (pp. 1–4). IEEE. (2021)
109. Sindhura, D., Pai, R. M., Bhat, S. N., & Pai, M. M.: Sub-Axial Vertebral Column Fracture CT Image Synthesis by Progressive Growing Generative Adversarial Networks (PGGANs). In 2022 International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER) (pp. 311–315). IEEE (2022)
110. Kang, H., Park, J.-S., Cho, K., Kang, D.-Y.: Visual and quantitative evaluation of amyloid brain PET image synthesis with generative adversarial network. Appl. Sci. **10**(7), 2628 (2020). https://doi.org/10.3390/app10072628
111. Shen, T., Hao, K., Gou, C., Wang, F.-Y.: Mass image synthesis in mammogram with contextual information based on GANs. In: Computer Methods and Programs in Biomedicine, **202**, 106019, ISSN 0169–2607 (2021). https://doi.org/10.1016/j.cmpb.2021.106019
112. Korkinof, D., Rijken, T., O'Neill, M., Yearsley, J., Harvey, H., Glocker, B.: High- resolution mammogram synthesis using progressive generative adversarial net- works. (2018). http://arxiv.org/abs/1807.03401
113. Denck, J., Guehring, J., Maier, A., Rothgang, E.: Enhanced magnetic resonance image synthesis with contrast-aware generative adversarial networks. J. Imaging **7**(8), 133 (2021). https://doi.org/10.3390/jimaging7080133
114. Han, C., et al.: GAN-based synthetic brain MR image generation. In: Proceeding of - International Symposium Biomedicene Imaging, vol. 2018-April, no. ISBI, pp. 734–738, (2018). https://doi.org/10.1109/ISBI.2018.8363678.
115. Bermudez, C., Plassard, A.J., Davis, L.T., Newton, A.T., Resnick, S.M., Landman, B.A.: Learning implicit brain MRI manifolds with deep learning. In: Medical Imaging, Image Processing, 10574. International Society for Optics and Photonics, p. 105741L (2018)
116. Ghassemi, N., Shoeibi, A., Rouhani, M.: Deep neural network with Generative Adversarial Networks pre training for brain tumor classification based on MR images. Biomed. Signal Process. Control **57**, 101678 (2020). https://doi.org/10.1016/j.bspc.2019.101678
117. Gab Allah, A.M., Sarhan, A.M., Elshennawy, N.M.: Classification of brain MRI tumor images based on deep learning PGGAN augmentation. Diagnostics. **11**(12), 2343 (2021). https://doi.org/10.3390/diagnostics11122343
118. Ahmad, B., Sun, J., You, Q., Palade, V., Mao, Z.: Brain tumor classification using a combination of variational autoencoders and generative adversarial networks. Biomedicines **10**(2), 223 (2022)

119. Vashisht, S., Sharma, B., & Lamba, S.: Alzheimer detection using CNN and GAN augmentation. In 2023 World Conference on Communication & Computing (WCONF) (pp. 1–5). IEEE (2023)
120. Beers, A., Brown, J., Chang, K., Campbell, J.P., Ostmo, S., Chiang, M.F., Kalpathy- Cramer, J.: High-resolution medical image synthesis using progressively grown generative adversarial networks. (2018). http://arxiv.org/abs/1510.07818v1
121. Zheng, C., Bian, F., Li, L., Xie, X., Liu, H., Liang, J., Chen, X., Wang, Z., Qiao, T., Yang, J., Zhang, M.: Assessment of generative adversarial networks for synthetic anterior segment optical coherence tomography images in closed-angle detection. Transl. Vis. Sci. Technol. **10**(4), 34 (2021). https://doi.org/10.1167/tvst.10.4.34
122. Madani, A., Moradi, M., Karargyris, A., Syeda-Mahmood, T.: Chest x-ray generation and data augmentation for cardiovascular abnormality classification. In: Medical Imaging: Image Processing, 10574. International Society for Optics and Photonics, p. 105741M (2018)
123. Salehinejad, H., Colak, E., Dowdell, T., Barfett, J., Valaee, S.: Synthesizing chest X-ray pathology for training deep convolutional neural networks. IEEE Trans. Med. Imaging **38**(5), 1197–1206 (2019). https://doi.org/10.1109/TMI.2018.2881415
124. Venu, S.K., Ravula, S.: Evaluation of deep convolutional generative adversarial networks for data augmentation of chest X-ray images. Future Internet **13**, 8 (2021). https://doi.org/10.3390/fi13010008
125. Segal, B., Rubin, D.M., Rubin, G., et al.: Evaluating the clinical realism of synthetic chest X-rays generated using progressively growing GANs. SN Comput. Sci. **2**, 321 (2021). https://doi.org/10.1007/s42979-021-00720-7
126. Fujioka, T., et al.: Breast ultrasound image synthesis using deep convolutional Generative Adversarial Networks. Diagnostics **9**(4), 1–9 (2019). https://doi.org/10.3390/diagnostics9040176
127. Wang, Z., et al.: Intelligent glaucoma diagnosis via active learning and adversarial data augmentation. Chinese Academy of Scie," 2019 IEEE 16th Int. Symp. Biomed. Imaging (ISBI 2019), no. Isbi, pp. 1234–1237 (2019)
128. Hartanto, C.A., Kurniawan, S., Arianto, D., Arymurthy, A. M.: DCGAN-generated Synthetic Images Effect on White Blood Cell Classification. 012033 (2021). https://doi.org/10.1088/1757-899X/1077/1/012033
129. Che, H., Ramanathan, S., Foran, D.J., Nosher, J.L., Patel, V.M., Hacihaliloglu, I.: Realistic ultrasound image synthesis for improved classification of liver disease. ISBN 978–3–030-87582-4, ISBN 978-3-030-87583-1 (eBook), Simplifying Medical Ultrasound, pp. 179–188 (2021)
130. Mutepfe, F., Kalejahi, B.K., Meshgini, S., Danishvar, S.: Generative adversarial network image synthesis method for skin lesion generation and classification. J. Med. Signals Sens. **11**(4), 237–252 (2021). https://doi.org/10.4103/jmss.JMSS_53_20
131. Lahiri, A., Jain, V., Mondal, A., Biswas, P.K.: Retinal vessel segmentation under extreme low annotation: a generative adversarial network approach. (2018). http://arxiv.org/abs/1809.01348
132. Kang, L., Jiang, J., Huang, D., Huang, J., Zhang, T.: Retinal image synthesis with a double stage generative adversarial network. J. Med. Imaging Health Inform. **11**(9), 2383–2391 (2021)
133. Teramoto, A., et al.: Deep learning approach to classification of lung cytological images: two-step training using actual and synthesized images by progressive growing of generative adversarial networks. PLoS ONE **15**(3), 1–12 (2020). https://doi.org/10.1371/journal.pone.0229951
134. S. W. B et al.: OR 2.0 Context-Aware Operating Theaters, Computer Assisted Robotic Endoscopy, Clinical Image-Based Procedures, and Skin Image Analysis, vol. **11041**. Springer International Publishing. (2018)
135. Abdelhalim, I.S.A., Mohamed, M.F., Mahdy, Y.B.: Data augmentation for skin lesion using self-attention based progressive generative adversarial network. Expert Syst. Appl. **165**, 113922 (2021). https://doi.org/10.1016/j.eswa.2020.113922. (**ISSN 0957-4174**)
136. Jiang, J., Hu, Y. C., Tyagi, N., Zhang, P., Rimner, A., Mageras, G. S., Deasy, J. O., & Veeraraghavan, H.: Tumor-aware, Adversarial Domain Adaptation from CT to MRI for Lung Cancer Segmentation. Medical image computing and computer-assisted intervention: MICCAI ... International Conference on Medical Image Computing and Computer-Assisted Intervention, **11071**, 777–785 (2018). https://doi.org/10.1007/978-3-030-00934-2_86
137. Zhang, Z., Yang, L., Zheng, Y.: Translating and segmenting multimodal medical volumes with cycle- and shape-consistency generative adversarial network. 9242–9251. (2018). https://doi.org/10.1109/CVPR.2018.00963
138. Huo, Y., Xu, Z., Moon, H., Bao, S., Assad, A., Moyo, T.K., Savona, M.R., Abramson, R.G., Landman, B.A.: Synseg-net: synthetic segmentation without target modality ground truth. IEEE Trans. Med. Imaging. **38**(4), 1016–1025 (2018)
139. Hiasa, Y., Otake, Y., Takao, M., Matsuoka, T., Takashima, K., Prince, J.L., Sugano, N., Sato, Y.: Cross-modality image synthesis from unpaired data using Cycle- GAN. In: International Workshop on Simulation and Synthesis in Medical Imag- ing. Springer, Cham (2018). http://arxiv.org/abs/1803.06629
140. Pan, Y., Liu, M., Lian, C., Zhou, T., Xia, Y., Shen, D.: Synthesizing missing PET from MRI with cycle-consistent generative adversarial networks for Alzheimer's disease diagnosis. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, pp. 455–463 (2018)
141. Jin, C.B., Kim, H., Liu, M., Jung, W., Joo, S., Park, E., Ahn, Y.S., Han, I.H., Lee, J.I., Cui, X.: Deep CT to MR synthesis using paired and unpaired data. Sensors (Basel, Switzerland) **19**(10), 2361 (2019). https://doi.org/10.3390/s19102361
142. Kang, S.K., An, H.J., Jin, H., et al.: Synthetic CT generation from weakly paired MR images using cycle-consistent GAN for MR-guided radiotherapy. Biomed. Eng. Lett. **11**, 263–271 (2021). https://doi.org/10.1007/s13534-021-00195-8
143. Peng, Y., Chen, S., Qin, A., Chen, M., Gao, X., Liu, Y., Miao, J., Gu, H., Zhao, C., Deng, X., Qi, Z.: Magnetic resonance-based synthetic computed tomography images generated using generative adversarial networks for nasopharyngeal carcinoma radiotherapy treatment planning. Radiother. Oncol. **150**, 217–224 (2020). https://doi.org/10.1016/j.radonc.2020.06.049. (**Epub 2020 Jul 3**)
144. Tomar, D., Lortkipanidze, M., Vray, G., Bozorgtabar, B., Thiran, J.-P.: Self-attentive spatial adaptive normalization for cross-modality domain adaptation. IEEE Trans. Med. Imaging **40**(10), 2926–2938 (2021). https://doi.org/10.1109/TMI.2021.3059265
145. Lapaeva, M., Saint-Esteven, A.L.G., Wallimann, P., Günther, M., Konukoglu, E., Andratschke, N., et al.: Synthetic computed tomography for low-field magnetic resonance-guided radiotherapy in the abdomen. Phys. Imaging Radiat. Oncol. **24**, 173–179 (2022)
146. Sun, B., Jia, S., Jiang, X., Jia, F.: Double U-Net CycleGAN for 3D MR to CT image synthesis. Int. J. Comput. Assist. Radiol. Surg. **18**(1), 149–156 (2023)
147. Choi, H., Lee, D.S.: Generation of structural MR images from amyloid PET: application to MR-less quantification. J. Nucl. Med. **59**(7), 1111–1117 (2018). https://doi.org/10.2967/jnumed.117.199414. (**Epub 2017 Dec 7**)
148. Maspero, M., et al.: Dose evaluation of fast synthetic-CT generation using a generative adversarial network for general pelvis MR-only radiotherapy. Phys. Med. Biol. **63**, 185001 (2018). https://doi.org/10.1088/1361-6560/aada6d

149. Yang, Q., Li, N., Zhao, Z., Fan, X., Chang, E.I., Xu, Y., et al.: MRI image-to-image translation for cross-modality image registration and segmentation (2018). http://arxiv.org/abs/1801.06940
150. Emami, H., Dong, M., Nejad-Davarani, S.P., Glide-Hurst, C.K.: Generating synthetic CTs from magnetic resonance images using generative adversarial networks. Med. Phys. (2018). https://doi.org/10.1002/mp.13047. (**Advance online publication**)
151. Ben-Cohen, A., Klang, E., Raskin, S., Soffer, S., Ben-Haim, S., Konen, E., Amitai, M., Greenspan, H.: Cross-modality synthesis from CT to PET using FCN and GAN networks for improved automated lesion detection. Eng. Appl. Artif. Intell. (2018). https://doi.org/10.1016/j.engappai.2018.11.013
152. Wei, W., et al.: Learning myelin content in multiple sclerosis from multimodal MRI through adversarial training. In Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics) (2018).https://doi.org/10.1007/978-3-030-00931-1_59
153. Ranjan, A., Lalwani, D., Misra, R.: GAN for synthesizing CT from T2-weighted MRI data towards MR-guided radiation treatment. Magn. Reson. Mater. Phys., Biol. Med. **35**(3), 449–457 (2022)
154. Qin, Z., Liu, Z., Zhu, P., Ling, W.: Style transfer in conditional GANs for cross-modality synthesis of brain magnetic resonance images. Comput. Biol. Med. **148**, 105928 (2022)
155. Bi, L., Kim, J., Kumar, A., Feng, D., Fulham, M.: Synthesis of Positron Emission Tomography (PET) images via multi-channel Generative Adversarial Networks (GANs). In: Molecular Imaging, Reconstruction and Analysis of Moving Body Organs, and Stroke Imaging and Treatment. Springer, pp. 43–51 (2017)
156. Armanious, K., Jiang, C., Fischer, M., Küstner, T., Hepp, T., Nikolaou, K., Gatidis, S., Yang, B.: MedGAN: Medical image translation using GANs. Comput. Med. Imaging Graph. **79**, 101684 (2020). https://doi.org/10.1016/j.compmedimag.2019.101684
157. Florkow M.C., et al.: Deep learning–based MR-to-CT synthesis: The influence of varying gradient echo–based MR images as input channels. Magn. Resonance Med. (2020)
158. Liu, Y., Chen, A., Shi, H., Huang, S., Zheng, W., Liu, Z., Zhang, Q., Yang, X.: CT synthesis from MRI using multi-cycle GAN for head-and-neck radiation therapy. Comput. Med. Imaging Graph. (2021). https://doi.org/10.1016/j.compmedimag.2021.101953
159. Abu-Srhan, A., Almallahi, I., Abushariah, M.A.M., Mahafza, W., Al-Kadi, O.S.: Paired-unpaired unsupervised attention guided GAN with transfer learning for bidirectional brain MR-CT synthesis. Comput. Biol. Med. (2021). https://doi.org/10.1016/j.compbiomed.2021.104763
160. Gu, Y., Zheng, Q.: A transfer deep generative adversarial network model to synthetic brain CT generation from MR images. Hindawi Wirel. Commun. Mobile Comput. **202**, 9979606 (2021). https://doi.org/10.1155/2021/9979606
161. Yan, S., Wang, C., Chen, W., Lyu, J.: Swin transformer-based GAN for multi-modal medical image translation. Front. Oncol. **12**, 942511 (2022)
162. Wang, J., Xie, G., Huang, Y., Lyu, J., Zheng, F., Zheng, Y., Jin, Y.: FedMed-GAN: federated domain translation on unsupervised cross-modality brain image synthesis. Neurocomputing **546**, 126282 (2023)
163. Jang, S. I., Lois, C., Thibault, E., Becker, J. A., Dong, Y., Normandin, M. D., et al.: Taupetgen: Text-conditional tau pet image synthesis based on latent diffusion models. arXiv preprint. (2023). arXiv:2306.11984
164. Sandfort, V., Yan, K., Pickhardt, P.J., Summers, R.M.: Data augmentation using generative adversarial networks (CycleGAN) to improve generalizability in CT segmentation tasks. Sci. Rep. (2019). https://doi.org/10.1038/s41598-019-52737-x
165. Stiehl, B., Lauria, M., Singhrao, K., Goldin, J., Barjaktarevic, I., Low, D., Santhanam, A.: Scalable quorum-based deep neural networks with adversarial learning for automated lung lobe segmentation in fast helical free-breathing CTs. Int. J. Comput. Assist. Radiol. Surg. (2021). https://doi.org/10.1007/s11548-021-02454-6
166. Jain, S., Indora, S., Atal, D.K.: Lung nodule segmentation using salp shuffled shepherd optimization algorithm-based generative adversarial network. Comput. Biol. Med. **137**, 104811 (2021). https://doi.org/10.1016/j.compbiomed.2021.104811
167. Li, M., Lian, F., Wang, C., Guo, S.: Dual adversarial convolutional networks with multilevel cues for pancreatic segmentation. Phys. Med. Biol. **66**, 175025 (2021). https://doi.org/10.1088/1361-6560/ac155f
168. Kan, C.N.E., Gilat-Schmidt, T., Ye, D.H.: Enhancing reproductive organ segmentation in pediatric CT via adversarial learning, p. 31 (2021). https://doi.org/10.1117/12.2582127
169. Nishiyama, D., Iwasaki, H., Taniguchi, T., Fukui, D., Yamanaka, M., Harada, T., Yamada, H.: Deep generative models for automated muscle segmentation in computed tomography scanning. PLoS One **16**(9), e0257371 (2021). https://doi.org/10.1371/journal.pone.0257371
170. Cui, H., Yuwen, C., Jiang, L., Xia, Y., Zhang, Y.: Bidirectional cross-modality unsupervised domain adaptation using generative adversarial networks for cardiac image segmentation. Comput. Biol. Med. **136**, 104726 (2021). https://doi.org/10.1016/j.compbiomed.2021.104726
171. Conze, P.H., Kavur, A.E., Cornec-Le Gall, E., Gezer, N.S., Le Meur, Y., Selver, M.A., Rousseau, F.: Abdominal multi-organ segmentation with cascaded convolutional and adversarial deep networks. Artif. Intell. Med. **117**, 102109 (2021). https://doi.org/10.1016/j.artmed.2021.102109
172. Xue, Y., Xu, T., Zhang, H., Long, L.R., Huang, X.: SegAN: adversarial network with multi-scale L_1 loss for medical image segmentation. Neuroinformatics **16**(3–4), 383–392 (2018). https://doi.org/10.1007/s12021-018-9377-x
173. Rezaei, M., Yang, H., Meinel, C.: Whole heart and great vessel segmentation with context-aware of generative adversarial networks. In: Bildverarbeitung für die Medizin 2018. Springer, pp. 353–358 (2018)
174. Kohl, S., Bonekamp, D., Schlemmer, H.-P., Yaqubi, K., Hohenfellner, M., Hadaschik, B., Radtke, J.-P., Maier-Hein, K.: Adversarial networks for the detection of aggressive prostate cancer. (2017). http://arxiv.org/abs/1702.08014
175. Zhao, M., Wang, L., Chen, J., Nie, D., Cong, Y., Ahmad, S., Ho, A., Yuan, P., Fung, S.H., Deng, H.H.: Craniomaxillofacial bony structures segmentation from MRI with deep-supervision adversarial learning. In: Int. Conf. Med. Image Comput. Comput. Interv., Springer, pp. 720–727 (2018)
176. Yuan, W., Wei, J., Wang, J., Ma, Q., Tasdizen, T.: Unified attentional Generative Adversarial Network for brain tumor segmentation from multimodal unpaired images, Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). 11766 LNCS 229–237 (2019). https://doi.org/10.1007/978-3-030-32248-9_26
177. Nema, S., Dudhane, A., Murala, S., Naidu, S.: RescueNet: an unpaired GAN for brain tumor segmentation. Biomed. Signal Process. Control **55**, 101641 (2020). https://doi.org/10.1016/j.bspc.2019.101641
178. Xinheng, Wu., Bi, L., Fulham, M., Feng, D.D., Zhou, L., Kim, J.: Unsupervised rain tumor segmentation using a symmetric-driven adversarial network. Neurocomputing (2021). https://doi.org/10.1016/j.neucom.2021.05.073. (**455,242-254,0925-2312**)
179. Cheng, G., Ji, H., He, L.: Correcting and reweighting false label masks in brain tumor segmentation. Med. Phys. **48**, 169–177 (2021). https://doi.org/10.1002/mp.14480

180. Wang, W., Wang, G., Wu, X., Ding, X., Cao, X., Wang, L., Zhang, J., Wang, P.: Automatic segmentation of prostate magnetic resonance imaging using generative adversarial networks. Clin. Imaging **70**, 1–9 (2021). https://doi.org/10.1016/j.clinimag.2020.10.014
181. Dai, X., Lei, Y., Wang, T., Dhabaan, A.H., McDonald, M., Beitler, J.J., Curran, W.J., Zhou, J., Liu, T., Yang, X.: Head-and-neck organs-at-risk auto-delineation using dual pyramid networks for CBCT-guided adaptive radiotherapy. Phys. Med. Biol. (2021). https://doi.org/10.1088/1361-6560/abd953
182. Güven, S.A., Talu, M.F.: Brain MRI high resolution image creation and segmentation with the new GAN method. Biomed. Signal Process. Control **80**, 104246 (2023)
183. Al Khalil, Y., Amirrajab, S., Lorenz, C., Weese, J., Pluim, J., Breeuwer, M.: On the usability of synthetic data for improving the robustness of deep learning-based segmentation of cardiac magnetic resonance images. Med. Image Anal. **84**, 102688 (2023)
184. Al Khalil, Y., Amirrajab, S., Lorenz, C., Weese, J., Pluim, J., Breeuwer, M.: Reducing segmentation failures in cardiac MRI via late feature fusion and GAN-based augmentation. Comput. Biol. Med. **161**, 106973 (2023)
185. Tennakoon, R., Gostar, A.K., Hoseinnezhad, R., Bab-Hadiashar, A.: Retinal fluid segmentation in OCT images using adversarial loss based convolutional neural networks. Proc. Int. Symp. Biomed. Imaging. (2018). https://doi.org/10.1109/ISBI.2018.8363842
186. Ouyang, J., Mathai, T.S., Lathrop, K., Galeotti, J.: Accurate tissue interface segmentation via adversarial pre-segmentation of anterior segment OCT images. Biomed. Opt. Express **10**, 5291 (2019). https://doi.org/10.1364/boe.10.005291
187. Schlegl, T., Seeböck, P., Waldstein, S.M., Langs, G., Schmidt-Erfurth, U.: f-AnoGAN, Fast unsupervised anomaly detection with generative adversarial networks. Med. Image Anal. **54**, 30–44 (2019). https://doi.org/10.1016/j.media.2019.01.010
188. Wang, J., Li, W., Chen, Y., Fang, W., Kong, W., He, Y., Shi, G.: Weakly supervised anomaly segmentation in retinal OCT images using an adversarial learning approach. Biomed. Opt. Express (2021). https://doi.org/10.1364/boe.426803
189. Jiang, H., Ma, Y., Zhu, W., Fan, Y., Hua, Y., Chen, Q., Chen, X.: cGAN-based lacquer cracks segmentation in ICGA image. In: Comput. Pathol. Ophthalmic Med. Image Anal., Springer, pp. 228–235 (2018)
190. Son, J., Park, S.J., Jung, K.H.: Towards accurate segmentation of retinal vessels and the optic disc in fundoscopic images with generative adversarial networks. J. Digit. Imag. **32**, 499–512 (2019). https://doi.org/10.1007/s10278-018-0126-3
191. Kadambi, S., Wang, Z., Xing, E.: WGAN domain adaptation for the joint optic disc-and-cup segmentation in fundus images. Int. J. Comput. Assist. Radiol. Surg. **15**(7), 1205–1213 (2020). https://doi.org/10.1007/s11548-020-02144-9
192. Guo, Y., Zhao, W., Li, S., Zhang, Y., Lu, Y.: Automatic segmentation of the pectoral muscle based on boundary identification and shape prediction. Phys. Med. Biol. (2020). https://doi.org/10.1088/1361-6560/ab652b
193. Yıldız, E., Arslan, A.T., Tas, A.Y., Acer, A.F., Demir, S., Sahin, A., Barkana, D.E.: Generative adversarial network based automatic segmentation of corneal subbasal nerves on in vivo confocal microscopy images. Transl. Vis. Sci. Technol. (2021). https://doi.org/10.1167/TVST.10.6.33
194. Gilbert, A., Marciniak, M., Rodero, C., Lamata, P., Samset, E., Mcleod, K.: Generating synthetic labeled data from existing anatomical models: an example with echocardiography segmentation. IEEE Trans. Med. Imaging **40**(10), 2783–2794 (2021). https://doi.org/10.1109/TMI.2021.3051806
195. Brion, E., Léger, J., Barragán-Montero, A.M., Meert, N., Lee, J.A., Macq, B.: Domain adversarial networks and intensity-based data augmentation for male pelvic organ segmentation in cone beam CT. Comput. Biol. Med. (2021). https://doi.org/10.1016/j.compbiomed.2021.104269
196. Kunapinun, A., Dailey, M.N., Songsaeng, D., Parnichkun, M., Keatmanee, C., Ekpanyapong, M.: Improving GAN learning dynamics for thyroid nodule segmentation. Ultrasound Med. Biol. **49**(2), 416–430 (2023)
197. Narayanan, S. J., Anil, A. S., Ashtikar, C., Chunduri, S., & Saman, S.: Automated brain tumor segmentation using GAN augmentation and optimized U-Net. In: Frontiers of ICT in Healthcare: Proceedings of EAIT 2022 (pp. 635–646). Singapore: Springer Nature Singapore (2023)
198. Havsteen, I., Ohlhues, A., Madsen, K.H., Nybing, J.D., Christensen, H., Christensen, A.: Are movement Artifacts in magnetic resonance imaging a real problem?—A narrative review. Front. Neurol. **8**, 232 (2017). https://doi.org/10.3389/fneur.2017.00232. (**Published 2017 May 30**)
199. Yi, X., Walia, E., Babyn, P.: Generative adversarial network in medical imaging: a review. Med. Image Anal. **58**, 101552 (2019). https://doi.org/10.1016/j.media.2019.101552
200. You, C., et al.: CT Super-resolution GAN constrained by the identical, residual, and cycle learning ensemble (GAN-CIRCLE). IEEE Trans. Comput. Imaging. (2018)
201. Kang, E., Koo, H.J., Yang, D.H., Seo, J.B., Ye, J.C.: Cycle-consistent adversarial denoising network for multiphase coronary CT angiography. Med. Phys. (2019). https://doi.org/10.1002/mp.13284
202. Liu, Z., Bicer, T., Kettimuthu, R., Gursoy, D., De Carlo, F., & Foster, I.: TomoGAN: low dose synchrotron x-ray tomography with generative adversarial networks: discussion. J. Optic. Soc. Am. A. Opt. Image Sci. **37**, 442 (2020). https://doi.org/10.1364/josaa.375595.
203. Zhang, X., Feng, C., Wang, A., et al.: CT super-resolution using multiple dense residual block-based GAN. SIViP **15**, 725–733 (2021). https://doi.org/10.1007/s11760-020-01790-5
204. Dashtbani Moghari, M., Zhou, L., Yu, B., Young, N., Moore, K., Evans, A., Fulton, R.R., Kyme, A.Z.: Efficient radiation dose reduction in whole-brain CT perfusion imaging using a 3D GAN: performance and clinical feasibility. Phys. Med. Biol. (2021). https://doi.org/10.1088/1361-6560/abe917
205. Wang, Y., Sun, Z.L., Zeng, Z., Lam, K.M.: TRCT-GAN: CT reconstruction from biplane X-rays using transformer and generative adversarial networks. Digital Signal Process. **140**, 104123 (2023)
206. Jiang, J., Feng, Y., Xu, H., & Zheng, J.: Low-dose CT reconstruction via optimization-inspired GAN. In ICASSP 2023–2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 1–5). IEEE (2023)
207. Rezaei, S.R., Ahmadi, A.: A GAN-based method for 3D lung tumor reconstruction boosted by a knowledge transfer approach. Multimed. Tools Appl. **82**(28), 44359–44385 (2023)
208. Ramanathan, S., Ramasundaram, M.: Low-dose CT image reconstruction using vector quantized convolutional autoencoder with perceptual loss. Sādhanā **48**(2), 43 (2023)
209. Liao, H., Huo, Z., Sehnert,W. J., Zhou, S. K.,& Luo, J.: Adversarial sparse-view CBCT artifact reduction. In Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics). (2018)
210. Seitzer, M., et al.: Adversarial and perceptual refinement for compressed sensing MRI reconstruction. In Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics) (2018).https://doi.org/10.1007/978-3-030-00928-1_27

211. Mardani, M., et al.: Deep generative adversarial neural networks for compressive sensing MRI. IEEE Trans. Med. Imaging **38**, 0001 (2019). https://doi.org/10.1109/TMI.2018.2858752
212. Kim, K.H., Do, W.J., Park, S.H.: Improving resolution of MR images with an adversarial network incorporating images with different contrast. Med. Phys. **47**, 0001 (2018). https://doi.org/10.1002/mp.12945
213. Chen, Y., Shi, F., Christodoulou, A. G., Xie, Y., Zhou, Z., & Li, D.: Efficient and accurate MRI super-resolution using a generative adversarial network and 3D multi-level densely connected network. In: Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics). (2018).https://doi.org/10.1007/978-3-03000928-1_11
214. Du, W., Tian, S.: Transformer and GAN-based super-resolution reconstruction network for medical images. Tsinghua Sci. Technol. **29**(1), 197–206 (2023)
215. Wang, Y., et al.: 3D conditional generative adversarial networks for high-quality PET image estimation at low dose. Neuroimage **174**, 0001 (2018). https://doi.org/10.1016/j.neuroimage.2018.03.045
216. Hu, R., & Liu, H.: TransEM: Residual Swin-Transformer based regularized PET image reconstruction. In: International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 184–193). Cham: Springer Nature Switzerland (2022)
217. Schlegl, T., Seebock, P., Waldstein, S.M., Schmidt-Erfurth, U., Langs, G.: Unsupervised anomaly detection with generative adversarial networks to guide marker discovery. In: International Conference on Information Processing in Medical Imaging 146–157 (2017)
218. Chen, X., Konukoglu, E.: Unsupervised detection of lesions in brain MRI using constrained adversarial auto-encoders. MIDL conference book, MIDL mIDL 2018 medical imaging with deep learning (2018)
219. Baur, C., Wiestler, B., Albarqouni, S., Navab, N.: Deep autoencoding models for unsupervised anomaly segmentation in brain MR images. International MICCAI brain lesion workshop: 161–169 (2018)
220. Baumgartner, C.F., Koch, L.M., Can Tezcan, K., Xi Ang, J., Konukoglu, E.: Visual feature attribution using Wasserstein GANs. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition 8309–8319 (2018)
221. Kohl, S., Bonekamp, D., Schlemmer, H.-P., Yaqubi, K., Hohenfellner, M., Hadaschik, B., et al.: Adversarial networks for the detection of aggressive prostate cancer. CoRR. (2017). https://arxiv.org/abs/1702.08014
222. Han, C., Rundo, L., Murao, K., Noguchi, T., Shimahara, Y., Milacski, Z.Á., Koshino, S., Sala, E., Nakayama, H., Satoh, S.: MADGAN: unsupervised medical anomaly detection GAN using multiple adjacent brain MRI slice reconstruction. BMC Bioinformatics **22**(Suppl 2), 31 (2021). https://doi.org/10.1186/s12859-020-03936-1
223. Reddy, M. V. K., Murjani, P. K., Rajkumar, S., Chen, T., & Chandrasekar, V. A.: Optimized CNN model with deep convolutional GAN for brain tumor detection. In Congress on Intelligent Systems (pp. 409–425). Singapore: Springer Nature Singapore (2022)
224. Alrashedy, H.H.N., Almansour, A.F., Ibrahim, D.M., Hammoudeh, M.A.A.: BrainGAN: brain MRI image generation and classification framework using GAN architectures and CNN models. Sensors **22**(11), 4297 (2022)
225. Wolleb, J., Sandkuhler, R., and Cattin, P. C.: Descargan: Disease-specific anomaly detection with weak supervision. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, pp. 14–24 (2020)
226. Nakao, T., Hanaoka, S., Nomura, Y., et al.: Unsupervised deep anomaly detection in chest radiographs. J. Digit. Imaging **34**, 418–427 (2021). https://doi.org/10.1007/s10278-020-00413-2
227. Zhao, H., Li, Y., He, N., Ma, K., Fang, L., Li, H., Zheng, Y.: Anomaly detection for medical images using self-supervised and translation consistent features. IEEE Trans. Med. Imaging (2021). https://doi.org/10.1109/TMI.2021.3093883
228. Udrea, A., Mitra, G.D.: Generative adversarial neural networks for pigmented and non-pigmented skin lesions detection in clinical images. In: 21st International Conference on Control Systems and Computer Science (CSCS), 364–368 (2017)
229. Tuysuzoglu, A., Tan, J., Eissa, K., Kiraly, A.P., Diallo, M., Kamen, A.: Deep adversarial context-aware landmark detection for ultrasound imaging. International conference on medical image computing and computer-assisted intervention: 151–158 (2018)
230. Kazeminia, S., Baur, C., Kuijper, A., van Ginneken, B., Navab, N., Albarqouni, S., Mukhopadhyay, A.: GANs for medical image analysis. Artif. Intell. Med. **109**, 101938 (2020). https://doi.org/10.1016/j.artmed.2020.101938
231. Fan, J., Cao, X., Xue, Z., Yap, P.-T., Shen, D.: Adversarial similarity network for evaluating image alignment in deep learning-based registration. International conference on medical image computing and computer-assisted intervention: 739–46 (2018)
232. Yan, P., Xu, S., Rastinehad, A.R., Wood, B.J.: Adversarial image registration with application for MR and TRUS image fusion. In: International workshop on machine learning in medical imaging, 197–204 (2018)
233. Hu, Y., Gibson, E., Ghavami, N., Bonmati, E., Moore, C.M., Emberton, M., et al.: Adversarial deformation regularization for training image registration neural networks. International conference on medical image computing and computer-assisted intervention: 774–782 (2018)
234. Koshino, K., Werner, R.A., Pomper, M.G., Bundschuh, R.A., Toriumi, F., Higuchi, T., Rowe, S.P.: Narrative review of generative adversarial networks in medical and molecular imaging. Ann. Transl. Med. **9**(9), 821 (2021). https://doi.org/10.21037/atm-20-6325
235. Tan, C., Zhu, J., & Lio', P.: Arbitrary scale super-resolution for brain MRI images. Artificial Intelligence Applications and Innovations: 16th IFIP WG 12.5 International Conference, AIAI 2020, Neos Marmaras, Greece, June 5–7, 2020, Proceedings, Part I, 583, 165–176. (2020).https://doi.org/10.1007/978-3-030-49161-1_15
236. Lyu, Q., Shan, H., Wang, G.: MRI super-resolution with ensemble learning and complementary priors. IEEE Trans. Comput. Imaging **6**, 615–624 (2020)
237. Sanchez, I., & Vilaplana, V.: Brain MRI super-resolution using 3D generative adversarial networks. (2018)
238. Uzunova, H., Ehrhardt, J., Jacob, F., et al.: Multi-scale GANs for memory-efficient generation of high-resolution medical images. (2019). Available online: https://arxiv.org/abs/1907.01376
239. Zhang, Q., Sun, J., Mok, G.S.P.: Low dose SPECT image denoising using a generative adversarial network. (2019). Available online: https://arxiv.org/abs/1907.11944
240. Yang, Q., Yan, P., Zhang, Y., et al.: Low-dose CT image denoising using a generative adversarial network with Wasserstein distance and perceptual loss. IEEE Trans. Med. Imaging **37**, 1348–1357 (2018)
241. Yi, X., Babyn, P.: Sharpness-aware low-dose CT denoising using conditional generative adversarial network. J. Digit. Imaging **31**, 655–669 (2018)
242. Wolterink, J.M., Leiner, T., Viergever, M.A., et al.: Generative adversarial networks for noise reduction in low-dose CT. IEEE Trans. Med. Imaging **36**, 2536–2545 (2017)

243. Li, J., Pepe, A., Gsaxner, C., Campe, G. V., & Egger, J.: A baseline approach for AutoImplant: the MICCAI 2020 cranial implant design challenge. In: Workshop on Clinical Image-Based Procedures (pp. 75-84). Cham: Springer International Publishing (2020)
244. AccelMR 2020 Prediction Challenge – AccelMR 2020 for ISBI (2020)
245. MRI White Matter Reconstruction | ISBI 2019/2020 MEMENTO Challenge
246. Souza, R., Lucena, O., Garrafa, J., Gobbi, D., Saluzzi, M., Appenzeller, S., et al.: An open, multi-vendor, multi-field-strength brain MR dataset and analysis of publicly available skull stripping methods agreement. Neuroimage **170**, 482–494 (2018)
247. Hssayeni, M.D., Croock, M.S., Salman, A.D., Al-khafaji, H.F., Yahya, Z.A., Ghoraani, B.: Intracranial hemorrhage segmentation using a deep convolutional model. Data **5**(1), 14 (2020)
248. Menze, B.H., Jakab, A., Bauer, S., Kalpathy-Cramer, J., Farahani, K., Kirby, J., et al.: The multimodal brain tumor image segmentation benchmark (BRATS). IEEE Trans. Med. Imaging **34**(10), 1993–2024 (2014)
249. Bakas, S., Akbari, H., Sotiras, A., Bilello, M., Rozycki, M., Kirby, J.S., et al.: Advancing the cancer genome atlas glioma MRI collections with expert segmentation labels and radiomic features. Sci. Data **4**(1), 1–13 (2017)
250. Bakas, S., Reyes, M., Jakab, A., Bauer, S., Rempfler, M., Crimi, A., et al.: Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge. arXiv preprint (2018). arXiv:1811.02629
251. Zbontar, J., Knoll, F., Sriram, A., Murrell, T., Huang, Z., Muckley, M. J., et al.: fastMRI: An open dataset and benchmarks for accelerated MRI. arXiv preprint. (2018). arXiv:1811.08839
252. Quellec, G., Lamard, M., Conze, P.H., Massin, P., Cochener, B.: Automatic detection of rare pathologies in fundus photographs using few-shot learning. Med. Image Anal. **61**, 101660 (2020)
253. Orlando, J.I., Fu, H., Breda, J.B., Van Keer, K., Bathula, D.R., Diaz-Pinto, A., et al.: Refuge challenge: a unified framework for evaluating automated methods for glaucoma assessment from fundus photographs. Med. Image Anal. **59**, 101570 (2020)
254. Fu, H., Li, F., Sun, X., Cao, X., Liao, J., Orlando, J.I., et al.: Age challenge: angle closure glaucoma evaluation in anterior segment optical coherence tomography. Med. Image Anal. **66**, 101798 (2020)
255. Kermany, D., Zhang, K., & Goldbaum, M.: Large dataset of labeled optical coherence tomography (oct) and chest x-ray images. Mendeley Data, 3(10.17632) (2018)
256. Kermany, D.S., et al.: Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell **172**(5), 1122–1131 (2018). (**e9**)
257. Gireesha, H., and N. S.: Thyroid nodule segmentation and classification in ultrasound images. (2015)
258. Aerts, H.J., Velazquez, E.R., Leijenaar, R.T., Parmar, C., Grossmann, P., Carvalho, S., et al.: Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach. Nat. Commun. **5**(1), 4006 (2014)
259. Wee, L. and Dekker, A.: Data from head-neck-radiomics-HN1. (2019)
260. Campello, V.M., Gkontra, P., Izquierdo, C., Martin-Isla, C., Sojoudi, A., Full, P.M., et al.: Multi-centre, multi-vendor and multi-disease cardiac segmentation: the M&Ms challenge. IEEE Trans. Med. Imaging **40**(12), 3543–3554 (2021)
261. Heller, N., Sathianathen, N., Kalapara, A., Walczak, E., Moore, K., Kaluzniak, H., et al.: The kits19 challenge data: 300 kidney tumor cases with clinical context, ct semantic segmentations, and surgical outcomes. arXiv preprint (2019). arXiv:1904.00445
262. Heller, N., et al.: Data from C4KC-KiTS (2019).
263. Zhuang, X.: Multivariate mixture model for myocardial segmentation combining multi-source images. IEEE Trans. Pattern Anal. Mach. Intell. **41**(12), 2933–2946 (2018)
264. Zhuang, X.: Multivariate mixture model for cardiac segmentation from multi-sequence MRI. In: International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 581–588). Cham: Springer International Publishing (2016)
265. Leclerc, S., Smistad, E., Pedrosa, J., Østvik, A., Cervenansky, F., Espinosa, F., et al.: Deep learning for segmentation using an open large-scale dataset in 2D echocardiography. IEEE Trans. Med. Imaging **38**(9), 2198–2210 (2019)
266. Rister, B., Shivakumar, K., Nobashi, T., & Rubin, D. L.: CT-ORG: CT volumes with multiple organ segmentations. Cancer Imaging Arch. (2019)
267. Bloch, N., Madabhushi, A., Huisman, H., Freymann, J., Kirby, J., Grauer, M., et al.: NCI-ISBI 2013 challenge: automated segmentation of prostate structures. Cancer Imaging Arch. **370**(6), 5 (2015)
268. Bilic1a, P., et al.: The liver tumor segmentation benchmark (LiTS). arXiv, abs/1901.0, (2019)
269. Zhao, J., Zhang, Y., He, X., & Xie, P.: Covid-ct-dataset: a ct scan dataset about covid-19. arXiv preprint. (2020). arXiv:2003.13865, 490(10.48550)
270. Wang, L. L., Lo, K., Chandrasekhar, Y., Reas, R., Yang, J., Burdick, D., et al.: Cord-19: The covid-19 open research dataset. ArXiv (2020)
271. Wang, L., Lin, Z.Q., Wong, A.: Covid-net: a tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. Sci. Rep. **10**(1), 19549 (2020)
272. Buda, M., Saha, A., Walsh, R., Ghate, S., Li, N., Święcicki, A., et al.: Detection of masses and architectural distortions in digital breast tomosynthesis: a publicly available dataset of 5,060 patients and a deep learning model. arXiv preprint. (2020). arXiv:2011.07995
273. Buda, M., Saha, A., Walsh, R., Ghate, S., Li, N., Święcicki, A.: Data from the breast cancer screening–digital breast tomosynthesis (bcs-dbt). Data from The Cancer Imaging Archive (2020)
274. Li, P., Wang, S., Li, T., Lu, J., HuangFu, Y., & Wang, D.: A large-scale CT and PET/CT dataset for lung cancer diagnosis. The cancer imaging archive (2020)
275. Jin, L., Yang, J., Kuang, K., Ni, B., Gao, Y., Sun, Y., et al.: Deep-learning-assisted detection and segmentation of rib fractures from CT scans: development and validation of FracNet. EBioMedicine **62**, 103106 (2020)
276. Löffler, M.T., Sekuboyina, A., Jacob, A., Grau, A.L., Scharr, A., El Husseini, M., et al.: A vertebral segmentation dataset with fracture grading. Radiol.: Artif. Intell. **2**(4), e190138 (2020)
277. Sekuboyina, A., Husseini, M.E., Bayat, A., Löffler, M., Liebl, H., Li, H., et al.: VerSe: a vertebrae labelling and segmentation benchmark for multi-detector CT images. Med. Image Anal. **73**, 102166 (2021)
278. Hossin, M., Sulaiman, M.N.: A review on evaluation metrics for data classification evaluations. Int. J. Data Min. Knowl. Manage. Process **5**(2), 1 (2015)
279. Müller, D., Soto-Rey, I., Kramer, F.: Towards a guideline for evaluation metrics in medical image segmentation. BMC. Res. Notes **15**(1), 210 (2022)
280. Salama, W.M., Aly, M.H.: Deep learning in mammography images segmentation and classification: Automated CNN approach. Alexandria Eng. J. **60**(5), 4701–4709 (2021). https://doi.org/10.1016/j.aej.2021.03.048. (**ISSN 1110-0168**)
281. Wang, X., Meng, X., Yan, S.: Deep learning-based image segmentation of cone-beam computed tomography images for oral lesion detection. J. Healthcare Eng. **2021**, 4603475 (2021). https://doi.org/10.1155/2021/4603475. (**7 pages**)

282. Chiang, C.H., Weng, C.L., Chiu, H.W.: Automatic classification of medical image modality and anatomical location using convolutional neural network. PLoS One **16**(6), e0253205 (2021). https://doi.org/10.1371/journal.pone.0253205
283. Lv, E., Liu, W., Wen, P., Kang, X.: Classification of benign and malignant lung nodules based on deep convolutional network feature extraction. J. Healthcare Eng. **2021**, 8769652 (2021). https://doi.org/10.1155/2021/8769652. (**11 pages**)
284. Alruwaili, M., Gouda, W.: Automated breast cancer detection models based on transfer learning. Sensors **22**(3), 876 (2022). https://doi.org/10.3390/s22030876
285. Gab Allah, A.M., Sarhan, A.M., Elshennawy, N.M.: Classification of brain MRI tumor images based on deep learning PGGAN augmentation. Diagnostics (Basel). **11**(12), 2343 (2021). https://doi.org/10.3390/diagnostics11122343
286. Uysal, F., Hardalaç, F., Peker, O., Tolunay, T., Tokgoz, N.: Classification of fracture and normal shoulder bone X-ray images using ensemble and transfer learning with deep learning models based on Convolutional Neural Networks. (2021)
287. Yang, D., Martinez, C., Visuña, L., et al.: Detection and analysis of COVID-19 in medical images using deep learning techniques. Sci. Rep. **11**, 19638 (2021). https://doi.org/10.1038/s41598-021-99015-3
288. Germain, P., et al.: Classification of cardiomyopathies from MR cine images using Convolutional Neural Network with transfer learning. Diagnostics (Basel, Switzerland) **11**(9), 1554 (2021). https://doi.org/10.3390/diagnostics11091554
289. Yang, D., Xu, D., Zhou, S.K., Georgescu, B., Chen, M., Grbic, S., Metaxas, D., Comaniciu, D.: Automatic liver segmentation using an adversarial image-to-image network. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, pp. 507–515 (2017)
290. Motamed, S., Rogalla, P., Khalvati, F.: Data augmentation using Generative Adversarial Networks (GANs) for GAN-based detection of Pneumonia and COVID-19 in chest X-ray images. Inform. Med. Unlocked. **27**, 100779 (2021). https://doi.org/10.1016/j.imu.2021.100