A Review on Medical Image Applications Based on Deep Learning Techniques

Ali H. Abdulwahhab [1,*], Noof T. Mahmood [2], Ali Abdulwahhab Mohammed [3], Indrit Myderrizi [4], and Mustafa Hamid Al-Jumaili [1,5]

[1] Department of Electrical and Computer Engineering, Altinbas University, Istanbul, Turkey
[2] Department of Medical Instruments Techniques Engineering, Albayan University, Baghdad, Iraq
[3] Department of Remote Sensing, Al-Karkh University of Science, Baghdad, Iraq
[4] Department of Electrical and Electronics Engineering, Istinye University, Istanbul, Turkey
[5] Renewable Energy Research Center (RERC), University of Anbar, Ramadi, Iraq
Email: ahabdulwahhab@gmail.com (A.H.A.); noof.t@albayan.edu.iq (N.T.M.); ali_abdulwahhab@kus.edu.iq (A.A.M.); indrit.myderrizi@istinye.edu.tr (I.M.); mustafa.hamid@uoanbar.edu.iq (M.H.A.-J.)
*Corresponding author

Abstract—**The integration of deep learning in medical image analysis is a transformative leap in healthcare, impacting diagnosis and treatment significantly. This scholarly review explores deep learning's applications, revealing limitations in traditional methods while showcasing its potential. It delves into tasks like segmentation, classification, and enhancement, highlighting the pivotal roles of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs). Specific applications, like brain tumor segmentation and COVID-19 diagnosis, are deeply analyzed using datasets like NIH Clinical Center's Chest X-ray dataset and BraTS dataset, proving invaluable for model training. Emphasizing high-quality datasets, especially in chest X-rays and cancer imaging, the article underscores their relevance in diverse medical imaging applications. Additionally, it stresses the managerial implications in healthcare organizations, emphasizing data quality and collaborative partnerships between medical practitioners and data scientists. This review article illuminates deep learning's expansive potential in medical image analysis, a catalyst for advancing healthcare diagnostics and treatments.**

***Keywords*—deep learning, machine learning, medical image analysis, high-quality medical image datasets**

I. Introduction

The realm of image processing stands as a pivotal means for executing diverse procedures on images, aiming to yield enhanced visuals or extract valuable information. Across medical imaging, techniques like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), mammography, ultrasound, Positron Emission Tomography (PET), and X-ray have long been instrumental in disease treatment, early diagnosis, and evaluation. The interpretation of medical images traditionally fell within the expertise of specialists adept at analysis and diagnosis. However, owing to the vast spectrum of pathologies, the susceptibility of human fatigue, and the inherent variability among experts leading to potential errors, the integration of computer-assisted methodologies has emerged as imperative, mitigating the likelihood of misdiagnosis.

The inadequacy of traditional machine learning algorithms in tackling the complexities inherent in medical imaging has become apparent. However, propelled by advancements in rapid processors, the intersection of deep learning and medical images now offers substantial promise. This synergy empowers accurate and efficient disease diagnosis, prevention, and treatment, supporting professionals in the medical domain.

Compared to methods incorporating machine learning, deep learning into medical image processing presents a wide range of transformative benefits. Traditional approaches often rely heavily on extraction of features and rule-based systems which can be time consuming and prone, to oversight due to the subtle nature of medical images. On the hand machine learning algorithms demonstrate a capacity to independently learn and identify complex patterns without explicit human involvement. This adaptability is particularly crucial in the field of imaging, where there is variability in how pathologies present. Machine learning systems powered by networks can automatically extract relevant features from extensive datasets enabling them to achieve exceptional accuracy in tasks such as image recognition and classification. Furthermore, these systems employ an end-to-end learning approach that eliminates the need for task allocation, streamlines processes, and reduces the risk of human error. The combination of machine learning and processors further enhances efficiency allowing for timely and precise disease diagnosis, prevention and treatment. In summary, machine learning methods offer a solution to overcome the

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limitations of approaches by effectively navigating the complexities involved in medical image analysis.

For decades, human superiority in recognizing and differentiating patterns within medical images stood unchallenged. Presently, sophisticated deep learning algorithms enable machines to interpret and discern these patterns, marking a paradigm shift [1]. Deep learning, a subset of Artificial Intelligence (AI) rooted in Machine Learning (ML), mimics the structural and functional principles inspired by the human mind [2].

Artificial intelligence based on deep learning, guided by algorithms and formed by hidden neural cells, has become an important aspect in data science, with applications found in image recognition, classification, language processing, robotics, and other fields [3]. The Deep Neural Network (DNN), a cornerstone of deep learning, autonomously learns and extracts features sans human intervention, contingent upon the availability of ample data for learning and extraction [4]. Deep learning systems, leveraging substantial datasets alongside profound experience, exhibit remarkable accuracy in executing tasks. Furthermore, these systems perform classification processes on raw data via end-to-end learning, thereby eradicating the need for manual task allocation.

The incorporation of AI in medical domains dates back to the previous century. However, inefficacies prevailed owing to hardware limitations and underdeveloped models. Notwithstanding, the evolution of artificial intelligence has witnessed substantial strides, bestowing physicians with potent tools for image-based medical processing.

This article endeavors to review the gamut of deep learning algorithms employed in medical image processing across various diagnostic domains. It comprehensively lists and discusses the utilization of algorithms such as CNN, DBN, and SAE, elucidating their applications in disease diagnosis, classification, image enhancement, segmentation, image generation, and conversion. Additionally, this review delineates three primary contributions to the amalgamation of medical image processing and deep learning:

Deep exploration of deep learning techniques in medical image analysis has been a significant focus, especially in segmentation and classification for disease diagnosis and treatment, particularly in medical imaging modalities such as MRI, CT scans, and X-rays.

A critical examination of the challenges and limitations encountered while employing deep learning techniques in medical image analysis. These challenges include the imperative need for high-quality data, the interpretability of deep learning models, and the potential biases within the training data. The article accentuates the necessity for collaboration between medical experts and data scientists to craft effective deep learning models tailored for medical image analysis.

An insight-based study covering various applications is currently being conducted, including brain tumor segmentation, breast cancer detection, skin cancer classification, and COVID-19 diagnosis. Moreover, it delves into the distinct datasets employed in medical image analysis, including the BraTS dataset for brain tumor segmentation and the COVID-CT dataset for COVID-19 diagnosis.

In essence, this article serves to elucidate the potential of deep learning techniques within medical image analysis while underscoring the pressing need for continued research to surmount the challenges and limitations confronting the field.

II. Medical Image Datasets

The dataset stands as a fundamental component significantly influencing the efficacy of a program employing deep learning algorithms. Its quality, including accurate labeling and proper construction, proves pivotal for effective learning [4]. Across diverse fields, large datasets are extensively utilized in processing medical images, acknowledged and endorsed by regulatory authorities as crucial for facilitating robust deep learning processes.

The NIH Clinic's Chest X-ray dataset boasts an extensive collection of over 112,120 chest X-ray images derived from more than 30,000 patients. This repository specifically identifies and labels 14 prevalent chest diseases through text mining techniques applied to the reports. However, it's essential to note that these disease tags might contain errors as they've been generated through natural language processing methodologies [5]. This dataset is freely accessible and serves as a valuable resource for academic research [5]. Fig. 1 provides a sample representation from the Chest X-ray dataset.

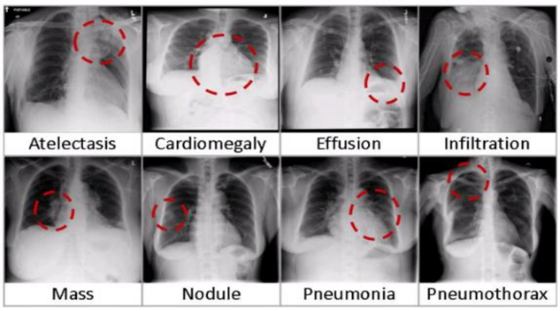


Fig. 1. NIH clinic's chest X-ray dataset [5].

The Cancer Imaging Archive (TCIA) stands as the National Cancer Institute's official repository, dedicated to housing cancer-related data. It meticulously upholds legal and technical protocols, employing robust anonymity measures to safeguard sensitive information [6]. This online repository serves as a comprehensive collection encompassing diverse datasets pertinent to cancer studies. Among its contents are a wide array of resources, including images, clinical data, and genomic information.

The BraTS dataset comprises data obtained from a competition showcased during conferences focusing on "Medical Image Computing" and "Computer-Assisted Intervention," emphasizing cutting-edge research in the field [7, 8]. This dataset features brain tumor images meticulously categorized by expert evaluators. The primary goal of the competition revolves around identifying the most effective algorithm capable of accurately segmenting tumors utilizing MR images.

Notably, in 2018, the competition expanded its focus to enhance predictions regarding patient survival. Fig. 2 provides an illustrative sample from the BraTS dataset.

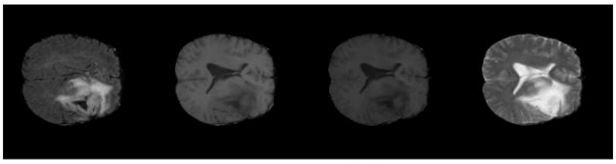
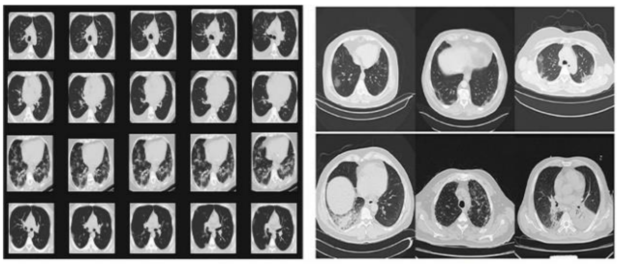


Fig. 2. BraTS dataset example.

The SARS-CoV2-CT and COVID-CT datasets play a crucial role in evaluating the effectiveness of CT scans for detecting COVID-19. Zhang *et al.* [9] conducted research focusing on diagnosing COVID-19 infection through the analysis of CT images. They used a COVID-CT dataset consisting of 349 CT scans collected from 216 individuals diagnosed with COVID-19. Similarly, Soares *et al.* [10] utilized the SARS-CoV-2 dataset to ascertain COVID-19 infection employing deep learning methodologies. This dataset includes CT images sourced from 60 individuals with confirmed COVID-19 and 60 individuals presenting diverse lung conditions. Fig. 3 offers a representative glimpse into the SARS-CoV2-CT and COVID-CT datasets.



(a) (b)

Fig. 3. SARS-CoV 2-CT and COVID-CT datasets' example. (a) SARS-CoV2-CT dataset, (b) COVID-CT.

The Digital Database for Screening Mammography (DDSM) is a robust repository specifically designed for breast cancer detection, covering more than 2,620 patient records [11]. Each scan within the DDSM encompasses approximately 10,480 mammogram data points, and meticulously categorized into three distinct classifications: normal, benign, and melanoma. Notably, these scans undergo thorough scrutiny and validation by specialized medical imaging professionals to ensure accuracy and reliability. The images within this database are captured and stored in JPEG format. Fig. 4 offers a representative sample showcasing mammography images from the DDSM dataset.

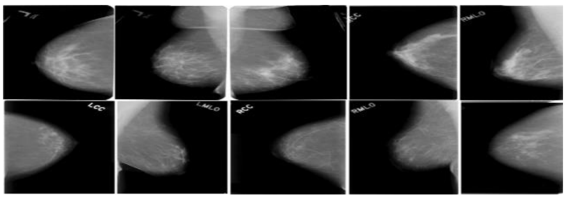


Fig. 4. DDSM dataset example.

III. Deep Learning Methods

Deep learning techniques include a variety of versatile algorithms that are widely used in many fields, including language analysis, recognition systems, and especially in the field of image processing. This study specifically delves into the realm of medical image processing algorithms. Within this domain, the focus is directed towards the utilization of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs). These sophisticated frameworks serve pivotal roles in tasks such as classification, segmentation, image generation, and enhancement.

A. Convolutional Neural Networks (CNN)

CNNs, known as Convolutional Neural Networks, stands as one of the most successful and prevalent types of deep learning architectures for image analysis and classification [12]. Initially developed by Fukushima in the late seventies, CNN's structure, characterized by multiple layers and the utilization of CNNs filters, processes inputs into smaller dimensions to extract essential features [13]. The evolution of CNNs for image analysis began in the last century, with significant milestones marking its progress.

Yann LeCun's work on LeNet in 1998 represented one of the earliest successful implementations of CNNs for recognizing text through back-propagation methods [14]. Despite these advancements, early CNNs faced limitations, necessitating multiple layers for extracting comprehensive visual features. Consequently, numerous subsequent algorithms sought to address these limitations and enhance deep learning systems.

In 2012, AlexNet proposed by Krizhevsky *et al.* [2] marked a significant leap, further advancing CNNs capabilities and continuing to shape the field. Subsequent developments such as VGGNet by Karen and Andrew [15], GoogLeNet by Christian *et al.* [8], ResNet by Kaining *et al.* [16], DenseNet by Gao Huang *et al.* [17], and EfficientNet by Mingxing and Quoc [18] showcased the continuous evolution of CNNs architectures, each introducing novel approaches and structures to enhance image classification.

The general CNNs structure for disease detection, as illustrated in Fig. 5, typically involves a sequence of layers: Convolutional, Activation, Pooling (comprising max and average pooling), Fully Connected, and Output layers [19]. The Convolutional layer, acting as the input layer, applies filters over the input image to generate feature maps by convolving the image [20]. These filters, with their specific coefficients, undergo iterative adjustments during training [3].

After passing through the convolution layers, the pooling layers, although optional, play a role in reducing dimensions and increasing computational efficiency, although with a slight loss of information [21, 22]. Meanwhile, the fully connected layer, which is the last layer of the network, combines the output of the previous layers with weights that have been determined through training based on a loss function [23]. This is an important process in the establishment and training of artificial neural networks for various image processing and pattern recognition tasks. Activation functions within this layer calculate classification probabilities, making CNNs a preferred choice for medical image classification, especially when leveraging large labeled datasets for improved accuracy [21].

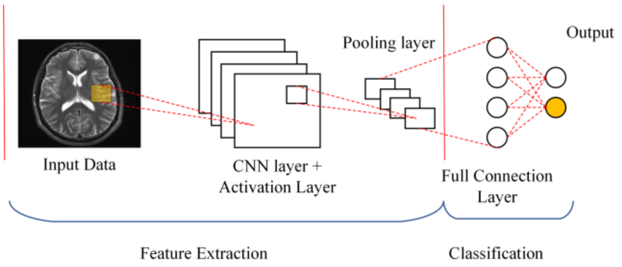


Fig. 5. General Convolutional Neural Networks (CNNs) architecture for brain disease detection

B. *Contested Producer Networks (CPN)*

In 2014, Goodfellow *et al.* [24] introduced the Generative Adversarial Network (GAN), aiming to expand image datasets and facilitate the transformation of textures or patterns from one image to another. Conceptually, this network operates as a manufacturer ("generator") striving to create realistic images and a "splitter" ("discriminator") discerning real from fake [24]. The GAN architecture comprises two adversarial models: the generator and the discriminator, engaged in a continual adversarial interplay, as illustrated in Fig. 6.

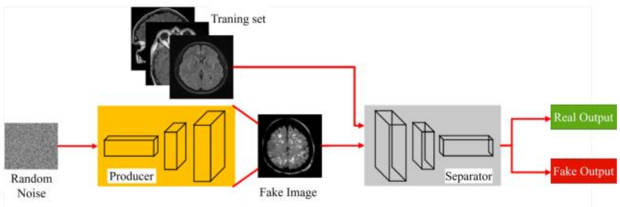


Fig. 6. Contested producer network architecture.

The discriminator's role lies in distinguishing between genuine and generated images, akin to traditional binary classification problems [25]. It produces a binary output (real/fake), guiding the generator in updating parameters to produce images that increasingly resemble genuine data.

Throughout its evolution, various GAN iterations have emerged to address diverse tasks in image manipulation. Cycle-GAN, employing two stacked GAN models, excels in transforming images across diverse concepts [26]. Utilizing CNNs in both its generator and discriminator, Cycle-GAN primarily works with image data. Meanwhile, the DC-GAN architecture focuses on image-to-image conversion, renowned for its effectiveness [27]. Patch-GAN is deployed in the discriminator to evaluate images by partitioning them into smaller sections, enhancing its discrimination capabilities [28]. Additionally, the Wasserstein GAN (W-GAN) model introduces the "Wasserstein Distance" in the GAN model, aiming to balance the training process and generate more consistent outcomes [29].

IV. Application of Deep Learning

This segment of the article delves into the multifaceted applications of deep learning algorithms in medical image analysis. It covers a spectrum of tasks including segmentation, classification, and disease diagnosis, showcasing the pivotal role played by deep learning in accurate and efficient medical diagnostics. Additionally, the article explores applications in medical image creation, enhancement, and transformation. These applications underscore the versatility and significance of Deep learning methodologies in revolutionizing medical image analysis for a spectrum of purposes, from precise diagnosis to innovative image enhancement techniques.

A. *Segmentation*

Segmentation means dividing the image into significant areas retaining various features [30]. It means extracting labels for each pixel and making predictions about these labels by some inference processes. It is used widely in separating the homogeneous regions for diagnosis and treatment's initial and critical components in medical image processing [23].

Previously, this process has been done using different filters and mathematical formulas. This field has been developed recently, and deep learning-based techniques for segmentation tasks have been adopted.

The segmentation process is vital in providing the essential features and information in CT and MRI medical images. It works on defining the organs or lesions' pixels [31].

Typically, CNN algorithms are utilized to do the segmentation process, the most prevalent deep learning technique employed in this sector [32]. The segmentation process helps analyze medical images in Computer-Aided-Diagnosis (CAD) systems. Also, classification models are used for segmentation, for example, "detection tumor or lesion based on segmentation, then determine their type using classification process".

Zheng *et al.* [33] made progress in localizing kidneys, on CT scans by using segmentation techniques. This approach provided insights into the variations in kidney shape. Also offered data augmentation. However, the study has some limitations that prevent an assessment of its novelty, such as not discussing how applicable the findings are to diverse datasets and not considering concerns related to data. Nevertheless, one of the strengths of this article is its exploration of data augmentation methods and the integration of Multi Step Learning (MSL), which enhances the proposed methodology and deepens our understanding of the topic.

In the field of pathology and microscope image analysis, Pan *et al.* [34] focused on improving nucleus detection using CNNs algorithms. Their approach, which centers around a scale fully convolutional neural network excels at detecting cells across various types and sizes with great versatility. Despite these strengths one notable weakness is that their work lacks comparisons with existing methods and provides details about their network training process. This absence of information limits reproducibility. A full understanding of their proposed approach.

Addressing pancreas segmentation in CT images, Farag *et al.* [35] utilized abdominal organs to generate data for developing computer aided tools.

Their methodology is notable for its thoroughness and competitive performance metrics, indicating promise in the field of pancreas segmentation. However, the article faces transparency challenges due to information about the dataset and a lack of aids that could improve readers understanding of the methods effectiveness. Providing dataset information and incorporating visualizations would strengthen the overall impact of the article.

Numerous enhancements have been made to CNN models resulting in segmentation processes. Long *et al.* [36] innovatively improved their models' capabilities by replacing the connecting layer with a Fully Convolutional Network (FCN) enabling intelligent pixel wise prediction of dense images. While the article effectively explains concepts particularly focusing on FCNs and providing an overview of their architecture and key components, it assumes a high level of reader knowledge and lacks a thorough discussion on FCNs limitations. The demonstrated practical effectiveness of FCNs is a strength. However, addressing limitations and making the content more accessible to a wider audience could further enhance the impact of the article. Zhou *et al.* [37] introduced an approach to segmenting 19 organs using a 2.5D Fully Convolutional Network (FCN) based on 3D CT images. The article highlights the effectiveness of their methodology the 2D FCN, with 3D voting in achieving accurate CT image segmentation. However, there are some weaknesses to consider, such as accuracy for structures and a limited focus on CT images without discussing how well the model generalizes to other imaging methods. The article addresses these limitations by providing comparisons and evaluations which contribute to its strength as a segmentation method. Sun *et al.* [38] proposed an approach using 3D Convolutional Networks (FCNs) for brain tumor segmentation in MRI images. Their work is notable for its methodology and unique multi pathway architecture contributing to the field. However, there are areas where improvement is needed, such as ensuring result reproducibility, comparing their method with existing approaches and providing visualizations to support their findings. Strengthening these aspects would enhance the impact of their work in the field of brain tumor segmentation.

Ronneberger *et al.* [39] expanded on the concept of Convolutional Networks (FCNs) by introducing the net model specifically designed for biomedical image segmentation.

The U net model, which has a shape resembling the letter "U", incorporates a contraction section that's similar, to CNN structures. This section includes activation functions (such as "ReLU") and pooling layers. Notably the expansion section of the U net receives output features from the contraction section allowing for the generation of an input image with the size and resolution. The U net, like FCNs uses a series of up sampling and downsampling layers that are connected through a hop connection process. This enhances the flow of information for accurate segmentation, as shown in Fig 7. Although the article presents an approach to image segmentation using U Net it lacks sufficient method comparisons and consideration of ethical implications. The strengths of this approach include an effective methodology, performance on challenging datasets and a comprehensive implementation with detailed evaluation metrics for U Net. To improve the contribution of the article, it would be beneficial to address implications more thoroughly and provide a more extensive comparison with existing methods. Additionally, visually explaining the architecture of U net would be helpful.

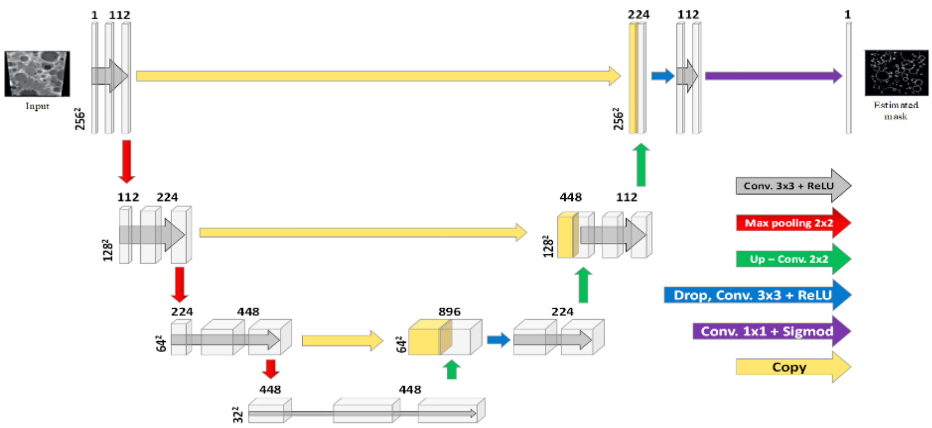


Fig. 7. U-net Architecture.

Çiçek *et al.* [40] have contributed to the development of the U-net structure by designing a 3-dimensional model specifically for volumetric segmentation. The model they developed has an approach that allows for precise separation of volumetric data in the field from 2-dimensional image slices. The authors who introduced a network specifically designed for volumetric segmentation, provide a theoretical analysis of its operation, and use the technique effective data enhancement. However, in order to make an impact in the field of image segmentation, it is important to address the identified shortcomings by conducting detailed comparisons with other methods that provide more applicable features and conducting diverse evaluations, thereby providing clearer motivation.

Different versions of the developed U-net model are used in the medical image, such as U-net++m RU-net and R2U-net Multi ResU-net, SAU-net, ASCU-net, and MRFU-net [41–46].

1) MRI image brain tumor segmentation

This section focuses on Brain tumor segmentation utilizing the BraTs-2020 dataset and the U-net model. The study's primary objective involves outlining the segmentation process for the tumor's core, leveraging the E1-Ce sequence MRI image, acquired using short-stroke radio frequencies, providing a clearer depiction of the tumor's core.

The MRI images are formatted in NIFTI and exhibit three axes: axial, coronal, and sagittal, with a pixel size of 240×240. Variations in pixel intensity within MRI images often necessitate normalization during preprocessing to facilitate effective model training.

Upon defining the tumor core's coordinates, the image is centered for cropping purposes. Subsequently, the entire 240×240 MR image is iteratively circled by *x* and *y* coordinates using a 64×64 frame. Regions displaying the highest density, indicative of potential tumor regions, are selected for the cropping process.

The cropping operation may involve multiple segments based on tumor size. The U-net model is trained using the cropped E1-Ce MRI image, and manual segmentation by radiologists provides the ground truth data.

The optimization algorithm, Adam, is employed during training, while the Dice Similarity Ratio serves as the model metric. This ratio is a statistical measure assessing the similarity between two datasets, commonly used in segmentation tasks. Following the training process, verification reveals Dice Similarity Ratio and sensitivity values of 68% and 80%, respectively.

Fig. 8 illustrates the cropping operation applied to the MRI image before its utilization in model training. The model predicts segmentation slices, with the actual slices presented alongside the clipped slices. The U-net model demonstrates similarity between its output and the labeled parts of the image. Table I showcases the success rates and methodologies employed in various brain tumor segmentation studies.

TABLE I. RECENT RESEARCH BASED ON BRAIN TUMOR SEGMENTATION

Ref.	Dataset	Method	Observations	Result
[47]	BraTS 2015	Deep Learning, CNN	Convolutional neural networks have been studied on MR images to identify various tumor types.	Dice Similarity Rate: 86.7% Accuracy: 98.33%
[48]	BraTS 2013 BraTS 2015 BraTS 2018	Deep Learning, CNN	In the first stage of the two-stage architecture, a multi-stage convolutional neural network architecture was developed (multi-cascaded convolutional neural network-MCCNN) to consider the local dependencies of the tags and perform rough segmentation. In the second stage, fully connected conditional random fields CRFs were used, taking into account the spatial context information, to eliminate some spurious outputs to provide more precise segmentation.	BraTS 2013: Whole tumor: 89% accuracy, 90% sensitivity, Core tumor: 82% accuracy, 84% sensitivity, Enlarged tumor: 77% accuracy, 86% sensitivity BraTS 2015: Whole tumor: 87% accuracy, 87% sensitivity, Core tumor: 76% accuracy, 74% sensitivity, Enlarged tumor: 75% accuracy, 80% sensitivity BraTS 2018: Whole tumor: 88.24% accuracy, 90.74% sensitivity, Core tumor: 74.81% accuracy, 76.21% sensitivity, Enlarged tumor: 71.78% accuracy, 86.84% sensitivity
[49]	BraTS 2015 BraTS 2017	Deep Learning, CycleGAN	An unpaired challenge training approach, an extended version of the cycleGAn architecture, is presented to segment the entire tumor and distinguish the core tumor region and other regions on the brain MR image. The proposed RescueNet (residual cyclic unpaired encoder-decoder network) uses residual and reflection principles. It has been stated that much less data is required for training.	BraTS 2015: Whole tumor: 94.01% accuracy, , Core tumor: 94.29% accuracy, Enlarged tumor: 87.32% accuracy, BraTS 2017: Whole tumor: 94.63% accuracy, Core tumor: 58.6% accuracy, Enlarged tumor: 93.54% accuracy.
[50]	BraTS 2020	Deep Learning, GAN	A contentious generator network architecture, called Vox2Vox that enables brain tumor segmentation from 3D volume to 3D volume is presented.	BraTS 2020: Whole tumor: 94.01% accuracy, 94.63% Harsdorf Similarity Ratio, Core tumor: 94.29% accuracy, 58.6% Harsdorf Similarity Ratio, Enlarged tumor: 87.32% accuracy, 93.54% Harsdorf Similarity Ratio
[51]	brain tumor dataset (figshare.com)	Deep Learning, CNN	A fully automated brain tumor segmentation and classification model using a Deep Convolutional Neural Network (DCNN), which includes a multi-scale approach, is presented.	Dice Similarity Rate: 82.8% Accuracy: 94%
present study	BraTS 2020	Deep Learning, CNN	Tumor segmentation was performed on MRI images in the T1 Ce sequence with U-net architecture. As normalization, the clipping algorithm was applied to the MR images.	Dice Similarity: Rate 86% Accuracy: 80%

B. Classification and Disease Diagnosis

Classification in medical imaging involves discerning the presence or absence of diseases within images, a critical process aiding in disease identification and classification, including distinguishing benign from malignant tumors. Deep learning techniques are extensively applied in this domain [52, 53].

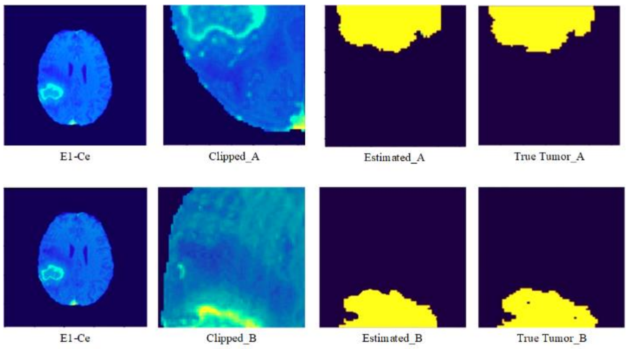


Fig. 8. Brain tumor segmentation sample results based on U-net.

The inception of deep learning in medical images dates to 2013 when Borsch and Tam introduced classification using Stacked Autoencoders (SAE) and RBM algorithms [54]. Significant progress has been made in the field of Alzheimer disease identification by researchers, such as Plis *et al.* [55], Suk and Shen [56], Suk *et al.* [57]. Alzheimer disease recognition applied Deep Belief Network (DBN) and Stacked Autoencoder (SAE) techniques based on MRI images. Plis *et al.* [55] provide an overview of deep learning methods. They lack an analysis of biological relevance and guidance on parameter selection. Suk and Shens innovative approach combine factor analysis with learning demonstrating novel methods with high accuracy, although there is a need for method comparisons and discussions on limitations [56]. Suk *et al.* [57] utilize a feature representation approach presenting a method description, but they also lack method comparisons and a clear definition of AD/MCI.

In the field of detection, Gulshan *et al.* [58] introduce an approach that utilizes CNN algorithms along, with a diverse dataset. Despite achieving accuracy metrics, the study lacks information regarding utility, data privacy considerations and ethical aspects. Similarly, Gargeya *et al.* [59] have made notable contributions to diabetic screening through various studies, showcasing impressive sensitivity and specificity metrics. However, these researches are still lacking in addressing the impact and comparing it with existing methods. Acknowledging the progress made by the CNN algorithm in detecting retinopathy, it is also important to address its limitations and note the caveats.

CNN algorithms have been widely applied in medical image analysis covering a range of applications. For instance, Lam *et al.* [60] focused on identifying retinopathy stages based on color fundus images achieving sensitivity and specificity equal to 95% and 94%, respectively However, their study lacked an assessment of utility and comparisons with methods. Similarly, Anton *et al.* [61] contributed to glaucoma identification with accuracy. However, they failed to compare their approach with existing methods or discuss related ethical issues. Chepala *et al.* [62] using Keras for brain tumor classification offered a user interface. However, they do not provide comparisons with other methods or details about pre-processing steps. Waghmare *et al.* [63] achieved accuracy in brain tumor classification. Did not provide detailed information about preprocessing steps or comparative analyses with alternative methods. Daz-Pernas *et al.* [51] achieving 97% accuracy in brain segmentation and classification like studies lacked details on preprocessing steps hyperparameter selection and comparative analyses. Finally, Nawaz *et al.* [64] focused on breast cancer detection using CNN models. However, they do not mention the details of image pre-processing. Make comparisons with other method.

Khan *et al*. [65] have discussed the classification of breast cancer using CNN architectures. However, they do not provide reasons for the parameters used. Make comparisons with existing methods. In another study, Zheng *et al.* [66] Developed the deep learning EABA model for brain tumor detection achieved 97% accuracy.

Several other studies have focused on cancer classification using CNN algorithms in types such as lung, prostate and skin cancers [67–73]. Zaid and Ghouti [67] proposed an automated pipeline for cancer classification. However, they did not compare it with existing methods or provide details about handling noisy images. Wu *et al.* [68] achieved accuracy in cancer classification, but lacked model interpretation and evaluation of generalization. Khan *et al.* [69] introduced a deep learning network based on CT image denoising and fusion for COVID-19 screening. While showcasing accuracy, they did not include comparisons or validation on datasets. Arvidsson *et al.* on the hand investigated the generalization of prostate cancer classification with accuracy, but lacked model interpretation and evaluation of generalization [70].

Sun *et al.* [71] and Lakshmanaprabu *et al.* [72] have successfully applied deep learning algorithms, for lung cancer diagnosis. They haven't provided thorough model interpretation and generalization assessment. Similarly, Heuvelmans *et al.* [73] achieved accuracy in lung cancer prediction using learning techniques, but they didn't offer detailed model interpretation or generalization evaluation. Although these studies contribute insights into cancer classification, it is essential to address these identified weaknesses to further improve the reliability and practicality of the proposed methodologies in clinical settings.

In skin cancer classification, Dorj *et al.* [74] made contributions by developing a CNN model that achieved remarkable accuracy, sensitivity and specificity. Their study utilized RGB images for classifying four types of skin cancer and demonstrated performance metrics. However, it's worth noting that their research lacks comparisons with existing methods or baselines for skin cancer classification and validation, on datasets or domains.

In the field of medical image analysis, deep learning applications have made advancements in addressing lung cancer, skin cancer and even playing a crucial role during the ongoing COVID-19 pandemic. Zheng and Qian [71] delve into lung cancer diagnosis using deep learning algorithms on a dataset. However, their work lacks analyses and exploration of hyperparameters.

Jinnai *et al.* [75] have contributed to the field of skin cancer classification through their region-based CNN model. Their approach achieves accuracy. It would be beneficial to see comparisons with state-of-the-art methods and a detailed analysis of hyperparameters. Shifting our attention to the context of COVID-19, Cai *et al.* [76, 77] have successfully quantified COVID-19 pneumonia using CT imaging with accuracy. However, it would be useful to have comparisons with techniques and exploration of hyperparameters for their Net approach. Wang *et al.* [78] have developed a deep learning algorithm for COVID-19 screening based on CT images demonstrating accuracy. Nonetheless, it would be valuable to include benchmarking and an analysis of hyperparameters in their study. Roy *et al.* [79] utilize learning for lung ultrasonography in the diagnosis of COVID-19 achieving results. However, it would be important to compare their method with existing approaches and explore hyperparameters further. Hemdan *et al.* [80] introduce a framework for COVID-19 diagnosis in X ray images using seven deep learning classifiers. While they emphasize timeliness, it is worth considering datasets for training models and conducting comparisons well as thorough hyperparameter analyses. Despite these studies limitations they collectively contribute to the evolving landscape of medical image analysis. Showcase the applications of deep learning in healthcare. It is crucial that future research addresses these identified weaknesses to ensure progress in this field. Table II summarizes various techniques and success rates for COVID-19 automatic detection based on deep learning.

Fig 9 showcases recent classification studies: (a) brain tumor analysis [51], (b) breast cancer identification [60], (c) skin cancer classification [81], and (d) distinguishing normal lung X-rays from COVID-19 infected lung X-rays [80]. These studies underscore the broad applicability of deep learning in medical image classification across diverse conditions.

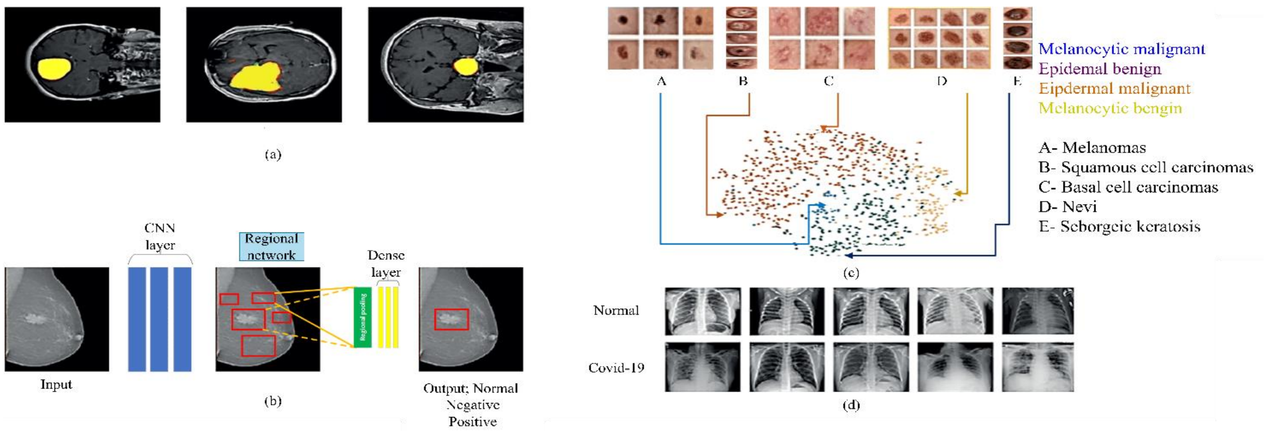


Fig. 9. Recent classification studies: (a) brain tumor analysis [51], (b) breast cancer identification [60], (c) skin cancer classification [80], and (d) distinguishing normal lung X-rays from COVID-19 infected lung X-rays [80].

C. *Medical Image Creation and Transformation*

Deep architectures play a pivotal role in medical applications, offering methods to enhance and manipulate algorithms for transforming data, particularly in generating information for areas with sparse data. In image conversion, 3D or 2D CNNs are widely employed, distinct from classification networks by lacking typical pooling layers. Instead, these networks are trained on paired input-output images, capturing the discrepancy between the outputs [82].

Qu *et al.* [83] introduced a deep learning network that synthesizes 7T T1 weighted MRI images from their 3T counterparts. This innovative approach combines information, from wavelet domains utilizing wavelet transformation and a Wavelet based Affine Transformation (WAT) layer. What sets this network apart is its ability to capture both local features resulting in improved image quality and impressive performance across metrics. In a vein, Li *et al.* [84] addressed the issue of MRI synthesis for MR guided radiotherapy. Their study employed learning models like CycleGAN, Pix2Pix and U Net to tackle this problem with remarkable success. However, one must consider the limitations stemming from an imbalanced dataset of brain tumor patients, which raises concerns about the generalization and robustness of the models used. Additionally, Nie *et al.* [85] presented an approach that converts MRI images to CT images using 3T 7T brain scans. The proposed method excels in generating target images while incorporating context techniques. Nonetheless it is worth noting that the use of imbalanced datasets in various medical imaging tasks may impact the broader applicability of this approach.

In the field of computer assisted diagnostics and physician training, the generation of images is widely used to enhance data diversity. A groundbreaking approach by Han *et al.* [86] introduced a Generative Adversarial

Network (GAN) method for creating synthetic brain MR images that possess characteristics compared to original scans. While the conditional GAN framework empowers users with control over the generation process and incorporates cycle consistency loss functions to maintain consistency, there are some limitations in this study. Specifically, the use of a homogeneous dataset consisting solely of healthy subjects raises concerns about how well this approach can be generalized or adapted for broader use. Similarly, Qiao *et al.* [87] proposed a context sensitive CorGAN network focused on medical image generation with an emphasis on 3D MR imaging. By leveraging a dataset from the Cancer Imaging Archive, their CorGAN model demonstrates its effectiveness in capturing temporal information through generators equipped with Long Short-Term Memory (LSTM) units and recurrent discriminators utilizing convolutional LSTM (ConvLSTM) units. The performance evaluation includes metrics such as mean error, peak signal to noise ratio, structural similarity index well, as visual quality assessment.

TABLE II. AUTOMATIC DETECTION OF COVID-19 DISEASE BY DEEP LEARNING FROM MEDICAL IMAGES

Ref.	Dataset	Type	Method	Results
[63]	A	Chest CT images	ResNet50, VGG16, Inception V3, DenseNet121, DenseNet201	Accuracy = 90 Precision = 60–70 Specificity = 60–70
[71]	B	Chest CT images	CNN, Decision trees	Accuracy = 82.9 Precision = 81 Specificity = 84
[75]	C	chest X-ray	Inception V3, Xception, and ResNet	F1-Score = 94 Accuracy = 95 Precision = 96 Recall = 91
[76]	D	Chest CT images	inception transfer-learning	Accuracy = 89.5 Sensitivity = 0.87 Specificity = 0.88
[78]	E	chest X-ray	VGG-19	F1-Score=100 Accuracy=96.3
[79]	F	Chest CT images, chest X-ray	VGGNet-19, ResNet50, InceptionV3, Xception	F1-Score = 90.5 Accuracy = 90 Precision = 91 Recall = 900.3
[80]	G	CT images	DenseNet	Accuracy = 92 Precision = 97 Specificity = 0.8

Note: A: https://nihcc.app.box.com/v/DeepLesion/folder/51877983116, https://nihcc.app.box.com/v/DeepLesion/folder/51877983116
B: Clinical dataset of 44 patients infected with COVID-19, 55 typical viruses
C: Chest X-ray (Covid-19 and Pneumonia) | Kaggle
D: collected CT images of 259 patients include; 180 cases viral pneumonia, 79 cases SARS-COV2. Also, 15 cases COVID-19
E: covid-chest x-ray-dataset/images at master · ieee8023/covid-chest x-ray-dataset · GitHub
F: https://github.com/UCSD-AI4H/COVID-CT/tree/master/Images-processed, https://www.kaggle.com/tawsifurrahman/covid19-radiography-database
G: CT image of the patient(146-COVID-2955) 19, 149 Normal

However, there are concerns regarding the ability of the CorGAN approach to generalize and remain robust due to the utilization of an unbalanced dataset. Fig. 10 illustrates various studies showcasing synthetic image generation methods.

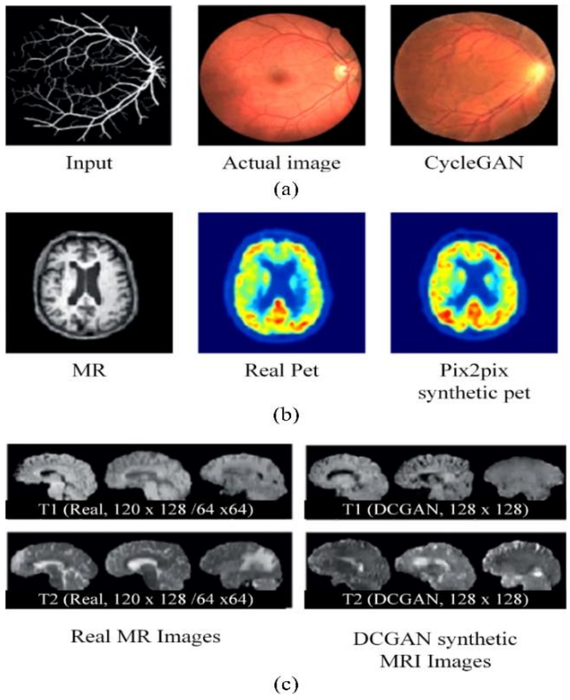


Fig. 10. Medical image creation with deep learning, (a) CycleGAN generating a retinal image [88], (b) pix2pix GAN model transforming MRI images into PET photos [89], (c) synthetic brain image created using the DCGAN model from T1 and 2T sequences [85].

D. Medical Images Enhancement

The quality of medical images significantly influences diagnostic accuracy in both manual assessments and computer-assisted systems. However, acquiring high-quality images is often impeded by the need for speedy acquisition and hardware limitations. Image enhancement techniques aim to refine digital images, employing methods like blurring, super-resolution, and noise reduction to elevate their quality, thereby enhancing various image analysis tasks, such as segmentation, classification, and detection.

In the field of medical image processing, Armanious *et al.* [90] utilized MedGAN to address PET CT noise issues and correct MRI artifacts. Their study demonstrated transparency adherence to established neuroimaging practices and the use of evaluation metrics, including the Alzheimers Disease Neuroimaging Initiative (ADNI) database. However, it is important to note that their research had limitations due to the use of a dataset with characteristics. This highlights the necessity for generalizability of the model. Additionally, concerns arise regarding the absence of alternative evaluation methods and scans showcasing abnormalities particularly in scenarios involving brain tumors.

Jifara *et al.* [91] introduced a feed forward Denoising Neural Network (DnCNN) for medical image denoising by incorporating batch normalization and residual learning techniques. Their article presents a methodology, clear explanations and comprehensive experimental results. Nevertheless, it is crucial to consider aspects related to privacy and data consent in their research. Furthermore, there is exploration of how their model generalizes across diverse medical imaging scenarios.

In the realm of medical image processing, Li *et al.* [92] proposed an enhanced neural network (3DECNN) aiming at improving spatial resolution in CT images. Their work showcases architecture along, with a description of the models details and thorough experimentation. However, there are some drawbacks to consider. One is the lack of discussion, which should be addressed. Additionally, the generalizability of the findings and the sensitivity of hyperparameters need exploration to ensure robustness across imaging scenarios [93]. In a study conducted by Yamashita and Markov [94], the focus was enhancing low-quality optic nerve head images captured with Optical Coherence Tomography (OCT) using Single Image Super Resolution (SR) networks such as Sparse Representation-based Convolutional Neural Network (SRCNN), Very Deep Super Resolution (VDSR), Deep Recursive Convolutional Network (DRCN), and Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN). The study provided a problem statement, an overview of SR networks and a transparent experimental setup. However, it is important to acknowledge that limitations such as training data, limited diversity in data sources and preliminary results may affect the applicability of their findings in real world scenarios [95]. Another interesting proposal was made by Raudonis *et al*. [96], who suggested a focal image fusion technique for enhancing early stage embryo images using a U-Net architecture. This study introduced an approach to fusion along with insights into hardware setup and comprehensive comparisons with alternative methods. However, the study presented some weaknesses that need to be addressed. Among these are the lack of exploration of how this method can be applied to various types of data, the absence of subjective comparisons of formalized images, and the lack of discussion of the limitations and challenges faced by the U-Net architecture. Additionally, a more in-depth examination of the trade-off between processing speed and image clarity is needed. Fig. 11 illustrates the transformative capabilities of deep learning in medical images.

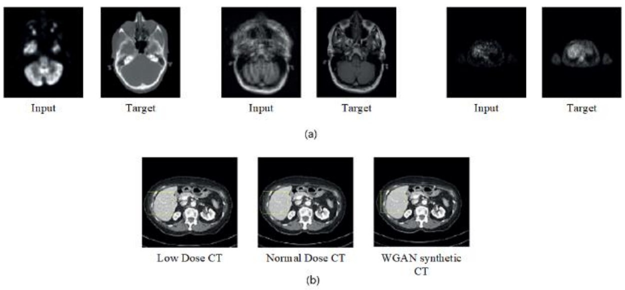


Fig. 11. Medical image creation and enhancement with deep learning, (a) MedGAN’s PET to CT scan conversion, addressing MRI motion artifacts and noise reduction [97, 98], (b) using WGAN to remove noise from low-dose radiation images, subsequently converting them into standard CT scans [93].

V. CONCLUSION

Deep learning stands as a prevalent technique in imaging analysis, offering diverse network architectures and algorithms that find applications in early diagnosis and treatment across various domains. Within healthcare, it serves as a tool for analyzing medical images, potentially reducing reliance on specialized expertise. While deep learning models confront challenges like data scarcity and suboptimal mathematical designs, a wealth of published studies underscores the technology’s enduring promise.

This article serves as a comprehensive guide to deep-learning techniques in medical image processing. It explores the pivotal roles of medical image segmentation and classification in disease diagnosis and treatment, spotlighting recent advancements fueled by deep learning algorithms. The coverage spans techniques and success rates in brain tumor segmentation, breast cancer detection, skin cancer classification, and COVID-19 diagnosis. Additionally, it delves into diverse deep learning algorithms like CNN, DBN, and SAE, showcasing their applicability across multiple medical imaging modalities, including MRI, CT, and X-ray. This piece aims to furnish a comprehensive overview of the technology’s multifaceted applications within the medical imaging landscape, catering to deep-learning users in this industry.

From a managerial standpoint, this article underscores how healthcare organizations and medical imaging companies can harness deep learning algorithms to elevate the precision and efficiency of medical image analysis, thereby enhancing disease diagnosis and treatment outcomes. The critical importance of data quality and quantity in shaping effective deep learning models is highlighted, providing healthcare managers with insights to prioritize data collection and management efforts. Moreover, the article emphasizes the pivotal role of collaboration between medical practitioners and data scientists in crafting impactful deep-learning models for medical image analysis, encouraging cross-disciplinary teamwork and fostering the adoption of these techniques in medical imaging practices.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

AHA and MHA wrote the research; NTM provided critical revisions; AAM contributed to the theoretical framework; IM reviewed and edited the manuscript; all authors approved the final version.

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REFERENCES

[1] A. Barragan-Montero, U. Javaid, G. Valdes *et al.*, "Artificial intelligence and machine learning for medical imaging: A technology review," *Physica Medica*, vol. 83, pp. 242–256, 2021.

[2] K. Alex, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017.

[3] S. Suganyadevi, V. Seethalakshmi, and K. Balasamy, "A review on deep learningin medical image analysis," *International Journal of Multimedia Information Retrieval*, vol. 11, no. 1, pp. 19–38, 2022.

[4] M. A. Abdou, "Literature review: Efficient deep neural networks techniques for medical image analysis," *Neural Computing and Applications*, vol. 34, no. 8, pp. 5791–5812, 2022.

[5] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, "Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," in *Proc. the IEEE Conference on Computer Vision and Pattern Recognition*, 2017, 2097–2106.

[6] K. Clark, B. Vendt, K. Smith *et al.*, "The Cancer Imaging Archive (TCIA): maintaining and operating a public information repository," *Journal of Digital Imaging*, vol. 26, pp. 1045–1057, 2013.

[7] B. H. Menze, A. Jakab, S. Bauer *et al.*, "The multimodal brain tumor image segmentation benchmark (BRATS)," *IEEE Transactions on Medical Imaging*, vol. 34, no. 10, pp. 1993–2024, 2014.

[8] B. Spyridon, M. Reyes, A. Jakab *et al.*, "Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge," arXiv preprint, arXiv:1811.02629, 2018.

[9] X. Yang, X. He, J. Zhao *et al.*, "COVID-CT-dataset: A CT scan dataset about COVID-19," arXiv preprint, arXiv:2003.13865, 2020.

[10] E. Soares, P. Angelov, S. Biaso *et al.*, "SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification," MedRxiv (2020): 2020-04.

[11] M. Heath, K. Bowyer, D. Kopans *et al.*, "The digital database for screening mammography," in *Proc. the Fifth International Workshop on Digital Mammography, M.J. Yaffe, ed.*, 2001, pp. 212–218.

[12] L. Alzubaidi, J. Zhang, A. J. Humaidi *et al.*, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, pp. 1–74, 2021.

[13] S.-C. B. Lo, H. P. Chan, J. S. Lin *et al.*, "Artificial convolution neural network for medical image pattern recognition," *Neural Networks*, vol. 8, pp. 1201–1214, 1995.

[14] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv preprint, arXiv:1409.1556, 2014.

[15] C. Szegedy, W. Liu, Y. Jia *et al.*, "Going deeper with convolutions," in *Proc. the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 1–9.

[16] K. He, X. Zhang, and S. Ren *et al.*, "Identity mappings in deep residual networks," in *Proc. Computer Vision–ECCV 2016: 14th European Conference*, Amsterdam, The Netherlands, October, 2016, pp. 11–14.

[17] K. He, X. Zhang, S. Ren *et al.*, "Deep residual learning for image recognition," in *Proc. the IEEE Conference on Computer Vision and Pattern Recognition*, 2016, pp. 770–778.

[18] M. Tan and L. Quoc, "Efficientnet: Rethinking model scaling for convolutional neural networks," in *Proc. International Conference on Machine Learning*, 2019, pp. 6105–6114.

[19] J. Naranjo-Torres, M. Mora, R. Hernández-García *et al.*, "A review of convolutional neural network applied to fruit image processing," *Applied Sciences*, vol. 10, 2020.

[20] D. Bhatt, C. Patel, H. Talsania *et al.*, "CNN variants for computer vision: history, architecture, application, challenges and future scope," *Electronics*, vol. 10, 2021.

[21] N. Aloysius and M. Geetha, "A review on deep convolutional neural networks," in *Proc. 2017 International Conference on Communication and Signal Processing (ICCSP), IEEE*, 2017, pp. 0588–0592.

[22] J. Wang, H. Zhu, S. H. Wang *et al.*, "A review of deep learning on medical image analysis," *Mobile Networks and Applications*, vol. 26, pp. 351–380, 2021.

[23] S. P. Singh, L. Wang, S. Gupta *et al.*, "3D Deep learning on medical images: A review," *Sensors*, vol. 20, 2020.

[24] P.-A. Goodfellow, M. Xu, W.-F. Ozair *et al.*, "Generative adversarial nets," *Advances in Neural Information Processing Systems*, vol. 27, 2014.

[25] H. Luo, M. Wang, P. K. Y. Wong *et al.*, "Full body pose estimation of construction equipment using computer vision and deep learning techniques," *Automation in Construction*, vol. 110, 2020.

[26] C. Baur, R. Graf, B. Wiestler *et al.*, "SteGANomaly: Inhibiting CycleGAN steganography for unsupervised anomaly detection in brain MRI," in *Proc. Medical Image Computing and Computer Assisted Intervention–MICCAI 2020: 23rd International Conference*, Lima, Peru, October, 2020, pp. 4–8.

[27] A. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," arXiv preprint, arXiv:1511.06434, 2015.

[28] I. Phillip, J. Y. Zhu, T. Zhou *et al.*, "Image-to-image translation with conditional adversarial networks," in *Proc. the IEEE Conference on Computer Vision and Pattern Recognition*, 2017.

[29] X. Xia, R. Togneri, F. Sohel *et al.*, "Auxiliary classifier generative adversarial network with soft labels in imbalanced acoustic event detection," *IEEE Transactions on Multimedia*, vol. 21, pp. 1359–1371, 2018.

[30] D. Suchismita, G. K. Nayak, L. Saba *et al.*, "An artificial intelligence framework and its bias for brain tumor segmentation: A narrative review," *Computers in Biology and Medicine*, vol. 143, 105273, Apr. 2022.

[31] M. H. Hesamian, W. Jia, X. He *et al.*, "Deep learning techniques for medical image segmentation: Achievements and challenges," *Journal of Digital Imaging*, vol. 32, pp. 582–596, 2019.

[32] P. Sharma, Y. P. S. Berwal, and W. Ghai, "Performance analysis of Deep learning CNN models for disease detection in plants using image segmentation," *Information Processing in Agriculture*, vol. 7, pp. 566–574, 2020.

[33] Y. Zheng, D. Liu, B. Georgescu, *et al.*, "Deep learning based automatic segmentation of pathological kidney in CT: local versus global image context," *Deep Learning and Convolutional Neural Networks for Medical Image Computing: Precision Medicine, High Performance and Large-Scale Datasets*, pp 241–255, 2017.

[34] X. Pan, D. Yang, L. Li *et al.*, "Cell detection in pathology and microscopy images with multi-scale fully convolutional neural networks," *World Wide Web*, vol. 21, pp. 1721–1743, 2018.

[35] A. Farag, L. Lu, H. R. Roth *et al.*, "Automatic pancreas segmentation using coarse-to-fine Superpixel labeling," *Deep Learning and Convolutional Neural Networks for Medical Image Computing: Precision Medicine, High Performance and Large-Scale Datasets*, pp. 279–302, 2017.

[36] J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," in *Proc. the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 3431–3440.

[37] X. Zhou, R. Takayama, S. Wang *et al.*, "Deep learning of the sectional appearances of 3D CT images for anatomical structure segmentation based on an FCN voting method," *Medical Physics*, vol. 44, no. 10, pp. 5221–5233, 2017.

[38] J. Sun, Y. Peng, Y. Guo *et al.*, "Segmentation of the multimodal brain tumor image used the multi-pathway architecture method based on 3D FCN," *Neurocomputing*, vol. 423, pp 34–45, 2021.

[39] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Proc. Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference*, Munich, Germany, October 2015, pp. 5–9.

[40] O. Cicek, A. Abdulkadir, S. S. Lienkamp *et al.*, "3D U-Net: Learning dense volumetric segmentation from sparse annotation," in *Proc. Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 19th International Conference*, Athens, Greece, October 2016, pp. 17–21.

[41] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh *et al.*, "Unet++: A nested u-net architecture for medical image segmentation," in *Proc. Deep learningin Medical Image Analysis and Multimodal Learning for Clinical Decision Support: 4th International Workshop, DEEP LEARNINGMIA 2018, and 8th International Workshop, ML-CDS* Granada, Spain, September 20, 2018, pp. 3–11.

[42] M. Z. Alom, M. Hasan, C. Yakopcic *et al.*, "Recurrent residual convolutional neural network based on u-net (r2u-net) for medical image segmentation," arXiv preprint, arXiv: 1802.06955, 2018.

[43] N. Ibtehaz and M. S. Rahman, "MultiResUNet: Rethinking the U-Net architecture for multimodal biomedical image segmentation," *Neural Networks*, vol. 121, pp. 74–87, 2020.
[44] J. Sun, F. Darbehani, M Zaidi *et al.*, "Saunet: Shape attentive u-net for interpretable medical image segmentation," in *Proc. Medical Image Computing and Computer Assisted Intervention–MICCAI 2020: 23rd International Conference*, Lima, Peru, October 2020, pp. 4–8.
[45] X. Tong, J. Wei, B. Sun *et al.*, "ASCU-Net: Attention gate, spatial and channel attention U-Net for skin lesion segmentation," *Diagnostics*, vol. 11, no. 3, pp. 501, Mar.2021.
[46] C. Li, J. Zhang, X. Zhao *et al.*, "MRFU-Net: A multiple receptive field U-Net for environmental microorganism image segmentation," *Information Technology in Biomedicine*, pp. 27–40, 2020.
[47] A. El Kader Isselmou, G. Xu, S. Zhang *et al.*, "Deep learning algorithm for brain tumor detection and analysis using MR brain images," in *Proc. the 2019 International Conference on Intelligent Medicine and Health*, 2019, pp. 28–32.
[48] K. Hu, Q. Gan, Y. Zhang *et al.*, "Brain tumor segmentation using multi-cascaded convolutional neural networks and conditional random field," *IEEE Access*, vol. 7, pp. 92615–92629, 2019.
[49] S. Nema, A. Dudhane, S. Murala *et al.*, "RescueNet: An unpaired GAN for brain tumor segmentation," *Biomedical Signal Processing and Control*, vol. 55, pp. 101641, Jan. 2020.
[50] M. D. Cirillo, and D. Abramian, and A. Eklund, "Vox2Vox: 3D-GAN for brain tumour segmentation," in *Proc. Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: 6th International Workshop, BrainLes 2020*, Lima, Peru, October 4, 2020, pp. 274–284.
[51] F. J. Diaz-Pernas, M. Martinez-Zarzuela, and M. Anton-Rodriguez *et al.*, "A Deep learning approach for brain tumor classification and segmentation using a multi-scale convolutional neural network," *Healthcare*, vol. 9, no. 2, 153, 2021.
[52] W. Wang, D. Liang, and Q. Chen *et al.*, "Medical image classification using deep learning," *Deep Learning in Healthcare: Paradigms and Applications*, pp. 33–51. 2020.
[53] K. Suzuki, "Overview of deep learning in medical imaging," *Radiological Physics and Technology*, vol. 10, no. 3, pp. 257–273, 2017.
[54] T. Brosch, R. Tam, and Alzheimer's Disease Neuroimaging Initiative, "Manifold learning of brain MRIs by deep learning," in *Proc. Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013: 16th International Conference*, Nagoya, Japan, September 2013, pp. 22–26.
[55] S. M. Plis, D. R. Hjelm, R. Salakhutdinov *et al.*, "Deep learning for neuroimaging: A validation study," *Frontiers in Neuroscience*, vol. 8, pp. 229, 2014.
[56] H. I. Suk and D. Shen, "Deep learning-based feature representation for AD/MCI classification," in *Proc. Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013: 16th International Conference*, Nagoya, Japan, 2013, pp. 22–26.
[57] H. I. Suk, S. W. Lee, D. Shen *et al.*, "Hierarchical feature representation and multimodal fusion with Deep learning for AD/MCI diagnosis," *NeuroImage*, vol. 101, pp. 569–582, 2014.
[58] V. Gulshan, L. Peng, M. Coram *et al.*, "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *Jama*, vol. 316, no. 22, pp. 2402–2410, 2016.
[59] R. Gargeya and T. Leng, "Automated identification of diabetic retinopathy using deep learning," *Ophthalmology*, vol. 124, pp. 962–969, 2017.
[60] C. Lam, D. Yi, M. Guo *et al.*, "Automated detection of diabetic retinopathy using deep learning," *AMIA Summits on Translational Science Proceedings*, 2018.
[61] J. J. Gomez-Valverde, A. Anton, G. Fatti *et al.*, "Automatic glaucoma classification using color fundus images based on convolutional neural networks and transfer learning," *Biomedical Optics Express*, vol. 10, no. 2, pp. 892–913, 2019.
[62] H. Ucuzal, S. Yaşar, C. Colak *et al.*, "Classification of brain tumor types by Deep learning with convolutional neural network on magnetic resonance images using a developed web-based interface," *in Proc. 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, 2019, pp. 1–5.
[63] V. K. Waghmare and M. H. Kolekar, "Brain tumor classification using deep learning," *Internet of Things for Healthcare Technologies*, pp.155–175, 2021.
[64] M. Nawaz, A. S. Adel, and T. H. A. Soliman. "Multi-class breast cancer classification using deep learning convolutional neural network," *Int. J. Adv. Comput. Sci. Appl*, vol.9, no.6, pp. 316–332, 2018.
[65] S. U. Khan, N. Islam, Z. Jan *et al.*, "A novel Deep learning based framework for the detection and classification of breast cancer using transfer learning," *Pattern Recognition Letters*, vol. 125, pp. 1–6, 2019.
[66] J. Zheng, D. Lin, Z. Gao *et al.*, "Deep learning assisted efficient AdaBoost algorithm for breast cancer detection and early diagnosis," *IEEE Access*, vol. 8, pp. 96946–96954, 2020.
[67] Z. Alyafeai and L. Ghouti, "A fully-automated Deep learning pipeline for cervical cancer classification," *Expert Systems with Applications*, vol. 141, pp. 112951, 2020.
[68] M. Wu, C. Yan, H. Liu *et al.*, "Automatic classification of cervical cancer from cytological images by using convolutional neural network," *Bioscience Reports*, vol. 8, no. 6, 2018.
[69] S. U. Khan, I. Ullah, N. Ullah *et al.*, "A novel CT image de-noising and fusion based deep learning network to screen for disease (COVID-19)," *Scientific Reports*, vol. 13, no. 1, pp. 6601, 2023.
[70] I. Arvidsson, N. C. Overgaard, F. E. Marginean *et al.*, "Generalization of prostate cancer classification for multiple sites using deep learning," in *Proc. 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, Apr 2018, pp. 191–194.
[71] W. Sun, B. Zheng, and W. Qian, "Computer aided lung cancer diagnosis with Deep learning algorithms," *Medical Imaging 2016: Computer-Aided Diagnosis*, vol. 9785, pp. 241–248, 2016.
[72] S. K. Lakshmanaprabu, S. N. Mohanty, and K. Shankar *et al.*, "Optimal deep learning model for classification of lung cancer on CT images," *Future Generation Computer Systems*, vol. 92, pp. 374–382, Mar. 2019.
[73] M. A. Heuvelmans, P. M. A. van Ooijen, and S. Ather *et al.*, "Lung cancer prediction by Deep learning to identify benign lung nodules," Lung *Cancer*, vol. 154, pp. 1–4, Apr. 2021.
[74] U. O. Dorj, K. K. Lee, J. Y. Choi *et al.*, "The skin cancer classification using deep convolutional neural network," *Multimedia Tools and Applications*, vol. 77, pp. 9909–9924, Apr. 2018.
[75] S. Jinnai, N. Yamazaki, Y. Hirano *et al.*, "The development of a skin cancer classification system for pigmented skin lesions using deep learning," *Biomolecules*, vol. 10, no. 8, 1123, 2020.
[76] W. Cai, T. Liu, X. Xue *et al.*, "CT quantification and machine-learning models for assessment of disease severity and prognosis of COVID-19 patients," *Academic Radiology*, vol. 27, no. 12, pp. 1665–1678, 2020.
[77] H. M. Haglan, A. S. Mahmoud, M. H. Al-Jumaili *et al.*, "New ideas and framework for combating COVID-19 pandemic using IoT technologies," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 22, no. 3, pp. 1565–1572, 2021.
[78] S. Wang, B. Kang, J. Ma *et al.*, "A Deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19)," *European Radiology*, vol. 31, pp. 6096–6104, 2021.
[79] S, Roy, W. Menapace, S. Oei *et al.*, "Deep learning for classification and localization of COVID-19 markers in point-of-care lung ultrasound," *IEEE Transactions on Medical Imaging*, vol. 39, no. 8, pp. 2676–2687, 2020.
[80] E. E. D. Hemdan, M. A. Shouman, and M. E. Karar, "COVIDX-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images," arXiv preprint, arXiv 2003.11055, 2020. doi: https://arxiv.org/pdf/2003.11055
[81] A. Esteva, B. Kuprel, R. A. Novoa *et al.*, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, 2017.
[82] G. Litjens, T. Kooi, B. E. Bejnordi *et al.*, "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.
[83] L. Qu, Y. Zhang, S. Wang *et al.*, "Synthesized 7T M.R.I. from 3T M.R.I. via deep learning in spatial and wavelet domains," *Medical Image Analysis*, vol. 62, 101663, 2020.
[84] W. Li, Y. Li, W. Qin *et al.*, "Magnetic Resonance Image (MRI) synthesis from brain Computed Tomography (CT) images based on deep learning methods for Magnetic Resonance (MR)-guided radiotherapy," *Quantitative Imaging in Medicine and Surgery*, vol. 10, no. 6, pp. 1223, 2020.

[85] D. Nie, R. Trullo, J. Lian *et al.*, "Medical image synthesis with deep convolutional adversarial networks," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 12, pp. 2720–2730, 2018.

[86] C. Han, H. Hayashi, L. Rundo *et al.*, "GAN-based synthetic brain MR image generation," in *Proc. the 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, April 2018, pp. 734–738.

[87] Z. Qiao, Z. Qian, H. Tang *et al.*, "CorGAN: Context aware recurrent generative adversarial network for medical image generation," in *Proc. 2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2020, pp. 1100–1103.

[88] S. Yao, J. Tan, Y. Chen *et al.*, "A weighted feature transfer GAN for medical image synthesis," *Machine Vision and Applications*, vol. 32, no. 1, pp. 1–11, 2021.

[89] M. M. Jung, B. van den Berg, E. Postma *et al.*, "Inferring PET from MRI with pix2pix," in *Proc. Benelux Conference on Artificial Intelligence*, 2018, vol. 9.

[90] W. Jifara, F. Jiang, S. Rho *et al.*, "Medical image denoising using convolutional neural network: A residual learning approach," *The Journal of Supercomputing*, vol. 75, no. 1, pp. 704–718, 2019.

[91] M. Li, S. Shen, W. Gao *et al.*, "Computed tomography image enhancement using 3D convolutional neural network," in *Proc. Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support: 4th International Workshop, DEEP LEARNINGMIA 2018*, Granada, Spain, 2018.

[92] O. A. Aldhaibani, M. H. AL-Jumaili, A. Raschella *et al.*, "A centralized architecture for autonomic quality of experience oriented handover in dense networks," *Computers & Electrical Engineering*, vol. 94, 107352, 2021.

[93] K. Yamashita and K. Markov, "Medical image enhancement using super resolution methods," in *Proc. Computational Science–ICCS 2020: 20th International Conference*, Amsterdam, The Netherlands, pp. 3–5, June 2020.

[94] M. Al-Jumaili and B. Karimi, "Maximum Bottleneck Energy Routing (MBER)—An energy efficient routing method for wireless sensor networks," in *Proc. the 2016 IEEE Conference on Wireless Sensors (ICWiSE)*, October 2016, pp. 38–44.

[95] V. Raudonis, A. Paulauskaite-Taraseviciene, K. Sutiene, "Fast multi-focus fusion based on deep learning for early-stage embryo image enhancement," *Sensors*, vol. 21, no.3, 2021.

[96] K. Armanious, C. Jiang, M. Fischer *et al.*, "MedGAN: Medical image translation using GANs," *Computerized Medical Imaging and Graphics*, vol. 79, 2020.

[97] Al-Jumaili, M. Hamid, H. M. Haglan, M. Kareem Mohammed, and Q. H. Eesee. "An automatic multi-axis solar tracking system in Ramadi city: Design and implementation," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 19, no. 3, pp. 1126–1234, 2020.

[98] B. Sutanu and P. K. Biswas, "Noise conscious training of non local neural network powered by self attentive spectral normalized Markovian patch GAN for low dose CT denoising," *IEEE Transactions on Medical Imaging*, vol. 12, pp. 3663–3673, 2021.