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Deep Learning for Medical Imaging – A Mini-Review

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Abstract: With every passing minute, new promising technologies provide us with more efficient and advanced techniques for transforming and enhancing of healthcare (HC) analytics. Medical images are a rich source of vital information that many physicians rely on. Continuous advancements in Artificial Intelligence (AI), notably Deep Learning (DL) approaches, are aiding in the identification, classification, and quantification of medical image patterns. Deep learning is the fastest growing topic in artificial intelligence and has recently been successfully applied in a variety of fields, including healthcare. Medical imaging (MI) research relies heavily on DL methods. DL can make a significant contribution to MI. DL approaches have been enabled in medical image analysis by employing computer-assisted imaging, providing a plethora of remedies and enhancements when radiologists and other professionals analyze them. DL networks may be effectively used in big data analytics for medical information discovery, knowledge deployment, and knowledge-based prediction. DL techniques have revitalized diagnosis and treatment procedures by automating and making them more competent and proficient. In this mini-review, DL methods are surveyed for MI and its possibilities for improving MI research are highlighted. An overview of basic DL principles is presented, as well as a brief outline of cutting-edge DL architectures used in the field of healthcare for the detection, classification, registration, and segmentation of medical images. A brief outline on the use of DL approaches in MI research is provided. Many well-known DL tools used for MI to improve healthcare in today's modern world are discussed. A comparison of the advantages and disadvantages of the most extensively used DL models is done. Finally, conclusions and future directions of DL for MI in healthcare sector are provided.

Keywords— *Deep Learning (DL); Medical Imaging (MI); Healthcare (HC); Machine Learning (ML); Artificial Intelligence (AI).*

I. Introduction

Health is at the top of the priority list in human life and it is the most important aspect of human existence. A productive lifestyle is inextricably linked to good health. A healthy lifestyle can aid in the prevention of chronic diseases and long-term ailments. Humans have contended with diseases that cause mortality throughout their lifetime. Humans are constantly combating a great number of diseases (such as COVID-19, HIV, Cancer, and so on), while also dramatically increasing the life expectancy and maintaining good health status. Historically, medicine was unable to cure a wide range of ailments due to a variety of factors ranging from clinical equipment and sensors to the analytical tools used to analyze medical data [1]. Because the healthcare sector is one in which everyone demands precision and accuracy regardless of cost, it is critical for individuals and companies operating in this field to give the best services available [2]. To provide improved quality of service (QoS), it is necessary to have a better awareness and correct knowledge of developing computational techniques to choose the optimal methodology that fulfills the expectations of the medical professional concerned.

Big data, artificial intelligence (AI), and cloud computing have all played significant roles in processing this data. Because of the quick development made in practically every aspect of our lives, AI has become widely known and widely used around the world [1]. AI is utilized to evaluate enormous amounts of historical data and derive insights that may be used to anticipate a patient's future cases using pattern recognition. AI applications and associated machine learning (ML) and deep learning (DL) models, clinical data, and image analysis may offer the most potential for making a positive, long-term impact on human lives in a relatively short period [3, 4]. In healthcare, DL techniques have several applications, including clinical decision support (CDS) systems, which use human expertise or massive datasets to make therapeutic suggestions. Image generation, image retrieval, image-based visualization, and image analysis are all part of the computer-based processing and examination of medical images [5].

In recent years, medical image processing has expanded to incorporate computer vision, pattern recognition, image mining, and machine learning in a variety of ways [6]. Deep learning is a popular way of determining the correctness of the future state. Deep learning is the process of learning patterns in data structures by utilizing neural networks comprised of numerous convolution nodes of artificial neurons [3]. DL has expanded the scope of medical image analysis. Deep learning applications in healthcare address a wide range of concerns, from cancer detection to infection monitoring to individualized therapy guidance [3]. A vast amount of data is now available to clinicians through various data sources such as radiological imaging, genetic sequencing, and pathological imaging. We are all in the process of converting all of this knowledge into usable information. The most common medical imaging (MI) modalities are X-ray, positron emission tomography (PET), computed tomography (CT), diffusion tensor imaging (DTI), magnetic resonance imaging (MRI), and functional MRI (fMRI) [1-3, 5].

To support doctors effectively, DL has become an assistive tool in medical image processing, with benefits such as error reduction, improved accuracy, rapid computation, and better diagnosis [1]. Due to quicker pattern detection from medical image data, DL aids clinicians in decision-making. It is now necessary for medical imaging researchers to completely adopt DL technology [7]. This mini-review gives an overview of key DL models and their applications in medical imaging. An overview of fundamental DL principles is provided, as well as a brief examination of cutting-edge DL models utilized in healthcare for the detection, classification, registration, and segmentation of medical images. A summary of the application of DL techniques in medical imaging research is presented. Many well-known DL application tools (and their timeline) for medical imaging are described to improve healthcare in today's modern world. The advantages and disadvantages and associated challenges of the most widely used DL models are highlighted. Finally, the conclusions and future directions of DL for medical imaging are discussed.

II. MEDICAL IMAGING

Medical imaging (MI) makes use of physical phenomena such as light or electromagnetic radiation, radioactivity, nuclear magnetic resonance (NMR), and ultrasound to create visual representations or images of external or internal tissues of the human body or a portion of the human body in a noninvasive or invasive procedure [8]. Imaging data constitutes approximately 90% of all healthcare data and is thus one of the most significant sources of evidence for clinical analysis and medical research.

A. Modalities of MI

A vast amount of data is now available to physicians via various data sources such as radiological imaging, genetic sequences, and pathological imaging. Medical images are multimodal and have high pixel resolution. X-ray radiography, mammography (MG), computed tomography (CT), histopathology, wireless capsule endoscopy (WCE), optical coherence tomography (OCT), ultrasound, magnetic resonance imaging (MRI), and digital pathology are the most regularly utilized imaging modalities in clinical medicine [8, 9]. Medical image analysis is the process of converting all of this information into usable information. The appropriate kind is determined by the type of intended medical application. Magnetic resonance imaging (MRI), computed tomography (CT) scans, functional MRI (fMRI), diffusion tensor imaging (DTI), and positron emission tomography (PET), as well as other modalities such as X-ray, Ultrasound, and histology slides, have become more basic and frequently employed MI modalities used for medical imagery in the healthcare sector [1]. Fig.1 shows some important modalities of MI. In nonstandard conditions, medical imaging data is segregated and captured. Although there are a great number of medical imaging data in the clinic, there is substantial diversity in terms of equipment and scanning settings due to a lack of standardized collection techniques, resulting in the so-called "distribution drift" issue [8]. Disease patterns in medical imaging are many, and their occurrence follows a bell-shaped distribution. Labels connected with medical photographs are frequently sparse and noisy. Medical image processing and analysis activities are broad and difficult. Medical imaging encompasses a wide range of duties. On a technological level, technologies as reconstruction, augmentation, restoration, classification, detection, segmentation, and registration are available (Fig. 1) [1, 8]. When deep learning architectures are integrated with several MI modalities and illness types, they should solve a huge number of very complicated tasks associated with numerous medical imaging applications. Such deep learning applications in healthcare address a wide range of concerns, from cancer detection to infection monitoring to individualized therapy guidance.

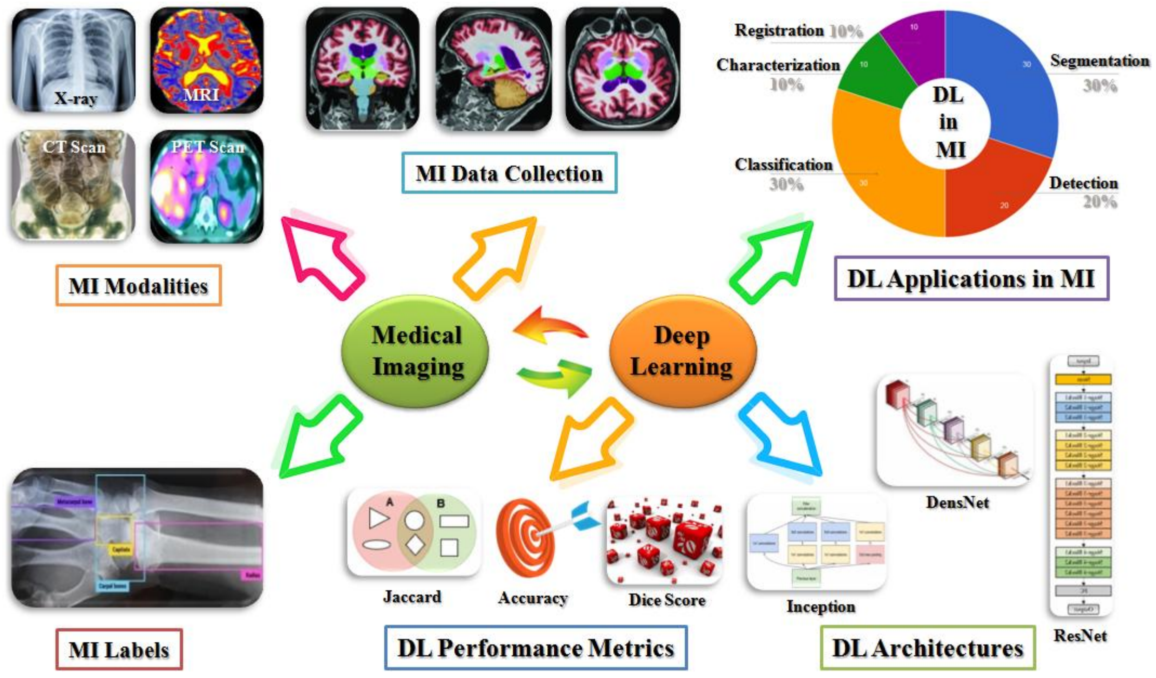

Fig. 1. Deep learning implementation and traits for medical imaging application

B. Clinical Requirements and MI Applications

Medical imaging is often used in clinical diagnosis and therapy. A radiologist typically evaluates the obtained medical images and makes a summary report of their findings. Based on the images and the radiologist's report, the referring physician develops a diagnosis and treatment plan. Human image interpretation, on the other hand, is restricted due to human mistakes in clinical data misinterpretation and analysis. AI techniques, such as deep learning, can help physicians by automating image analysis (Fig. 1) [1, 8]. Because of sophisticated real-time MI data visualization and quantification tools, DL can further expand physicians' skills to incorporate the characterization of three-dimensional (3-D) and time-varying events (dynamic MI data) in clinical reports.

III. DEEP LEARNING

Machine learning (ML) is an enthralling topic of research study in computer science and engineering [10]. ML is designated as an AI branch since it allows for the recognition of significant patterns in samples and then uses the identified pattern to forecast future data or make judgments under uncertain settings [2, 11, 12]. ML uses algorithms to compute image attributes deemed to be significant in producing the intended prediction or diagnosis of diseases [12]. Following that, the ML algorithms select the optimum combination of these image attributes for image classification or computation of some metric for the given image area. Deep learning (DL) is a subset of machine learning (ML) and a type of artificial neural network (ANN) that mimics multi-layered human cognition [2, 11]. The basic functional unit in neural networks is the 'neuron'. A neuron is a notion inspired by the human brain that accepts various signals as input, combines them linearly using weights, and then passes these combined signals via non-linear signals to form output signals [5]. DL is built on end-to-end learning, with the machine receiving an image dataset as input. The DL model is trained on the provided input, and neural networks find the underlying pattern of the medical images by extracting the prominent aspects of each item automatically. In MI analysis, DL is chosen over ML because it provides the benefit of automated feature extraction from medical images, which normal ML algorithms do not provide [2].

A. DL Architectures

The commonly known key categories of deep learning and their main subcategories are shown in Fig. 2a [1]. There are three important types of DL techniques: supervised learning (SL), unsupervised learning (USL), and semi-supervised learning (SSL). The supervising learning model is trained using a non-input output pair. The known value includes an input factor as well as the suggested value (supervisory signal) [6]. The supervising learning strategy takes advantage of current labels to break the labels of the desired output. Supervised learning is used to recognize faces, traffic symbols, and to translate voice to text. Semi-supervised learning is a technique that bridges the gap between unsupervised and supervised machine learning. Semi-supervised learning employs both labeled and unlabeled values. The small quantities of data are combined with the unlabeled data to improve learning accuracy. Unsupervised learning focuses on the interrelationships of dataset parts and employs labels to classify the data [7]. Some important DL architectures (RNN, RBM, CNN, GAN, RBM, AE) used in MI are described below (Fig. 2) [1]. These DL architectures are routinely used in the analysis of medical images for disease diagnosis and clinical applications.

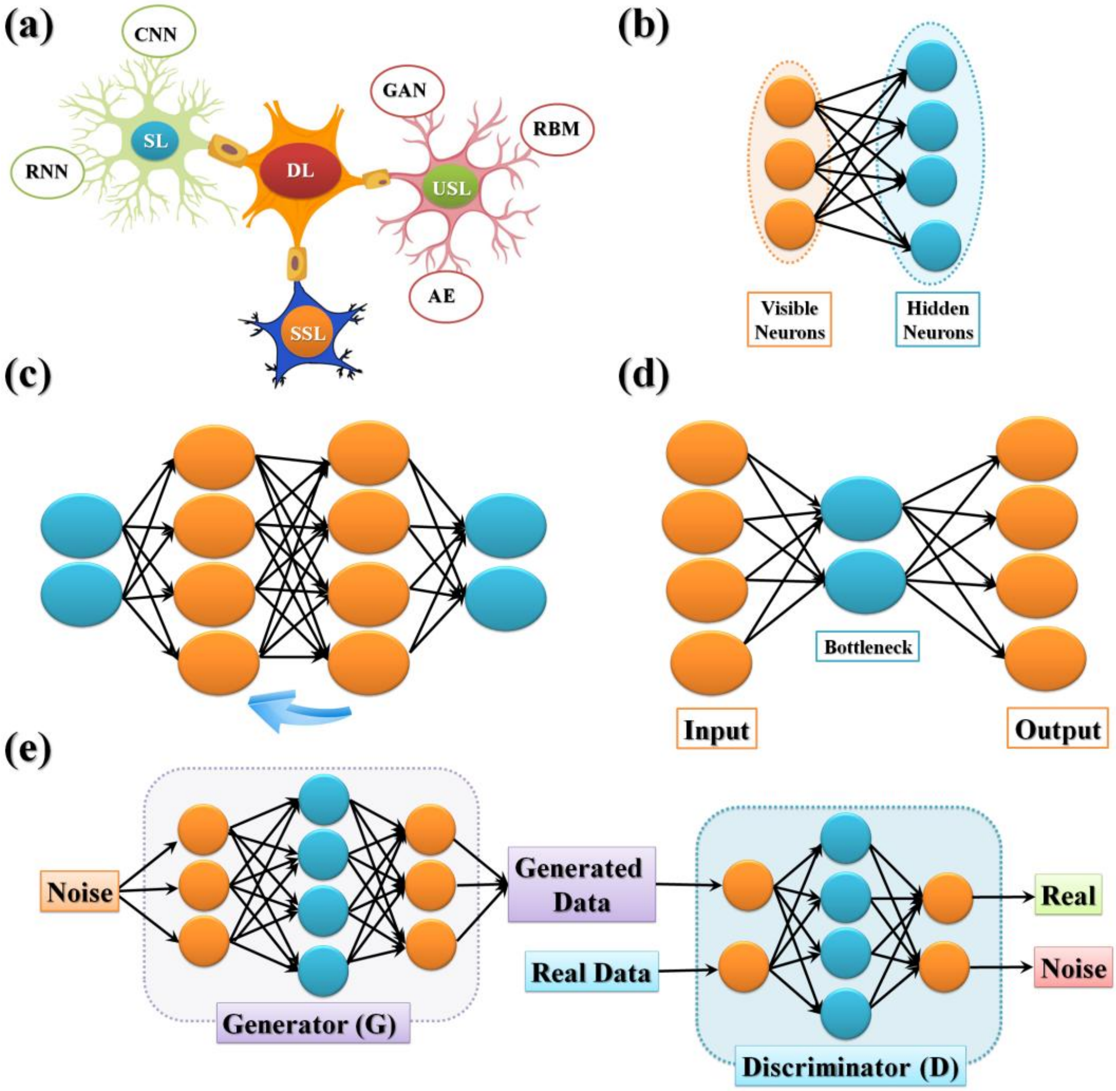

Fig. 2. A schematic of (a) basic DL architectures, (b) RBM, (c) RNN, (d) AE, and (e) GAN

1) *Convolutional Neural Networks (CNNs) :* CNNs are made up of several layers of neuron-like computational linkages. CNN's learning mechanism is modeled by mimicking the structure of the animal visual cortex [2]. CNN rose to prominence when the AlexNet model was successful due to its accuracy and low mistake rate in MI. CNN is utilized in COVID-19 detection utilizing X-rays/CT scans and has numerous MI applications such as the detection of skin lesions, tumors, heart abnormalities, blood cancer, breast cancer, eye, chest, etc [2].

2) *Restricted Boltzmann Machines (RBMs) :* RBMs are parameterized generative models based on probability. RBMs have two layers of NNs that can learn probability distributions and internal representations from datasets and have stochastic, generative, and probabilistic capabilities (Fig. 2b) [1]. RBM is suitable in MI due to breakthroughs in new learning algorithms and processing capacity. When utilized as building blocks for deep belief networks, RBMs garner more attention (DBNs) [2].

3) Recurrent neural networks (RNNs) : RNNs are neural networks that are appropriate for time series data and other sequential data because their pattern allows a network to establish dependence on past data, which is useful for predicting. RNN is recurrent, and the output of one layer is provided as input to the next layer's input (Fig. 2c) [1]. Medical diagnosis have made use of RNNs. RNN is utilized in an automated system to annotate diseases and forecast patients' heartbeats [2].

4) Autoencoders (AEs) : An autoencoder is an unsupervised learning approach that can automatically learn features from unlabeled input. An AE is made of an encoding path that provides extensive context information and a decoding path that allows information to be localized [2]. The AE architecture is shown in Fig. 2d [1]. The capacity to reconstruct output data that is identical to the input data is what gives autoencoders their resilience. AEs and their variants have demonstrated success in a wide range of areas, including image classification, pattern recognition, anomaly detection, etc [2].

5) Generative Adversarial Networks (GANs) : GANs are unsupervised models that are used to solve generative issues. GAN's major goal is to learn probability distributions from a set of training data using generative and discriminative models [2]**.** The generator network attempts to trick the discriminator network by creating data that are similar to legitimate data, while the discriminator network attempts to discriminate between the generator output and the actual data (Fig. 2e) [1]. GANs are widely used and successful in MI for image reconstruction, detection, and classification [2].

B. DL Milestones

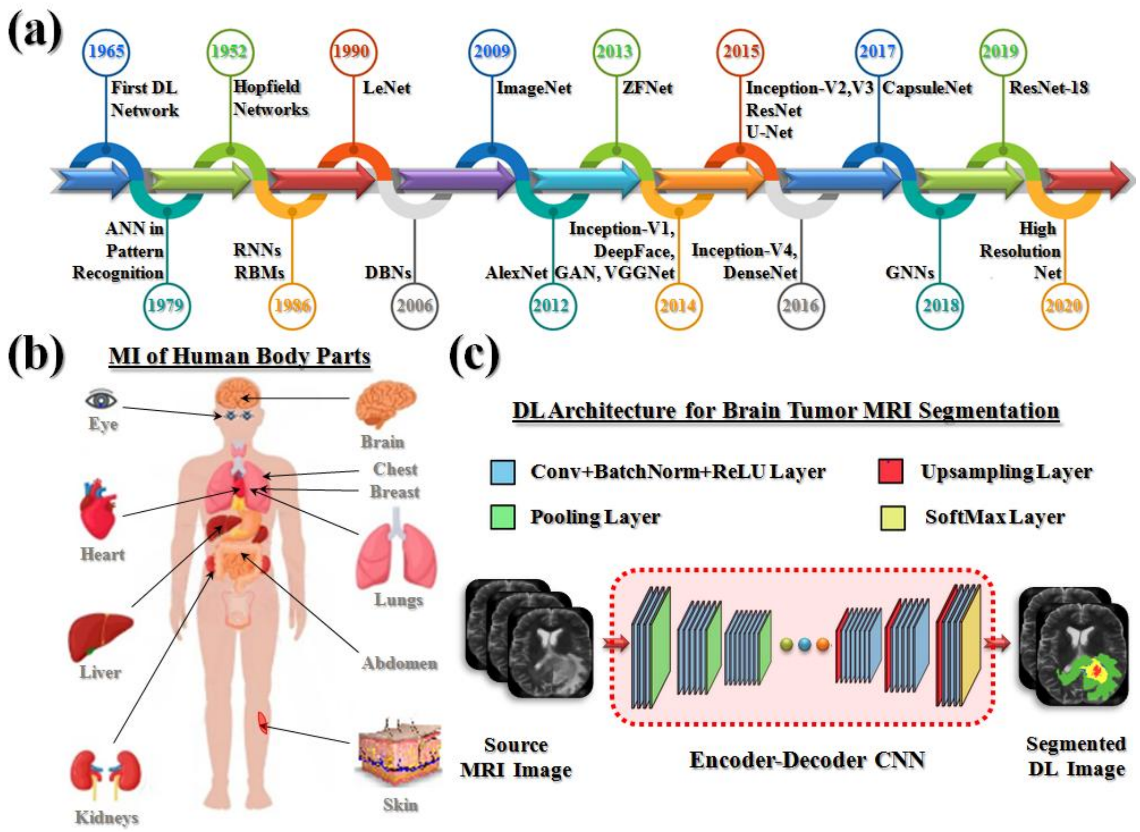

Fig. 3. A depiction of (a) DL milestones for MI, (b) important human body parts/organs for MI and (c) an illustration of CNN MRI segmentation process in diagnosis of brain tumor

Fig.3a outlines the milestones (development timeline) of DL in MI [1]. Some key DL advancements include ImageNet, ZFNet, AlexNet, GoogLeNet, Inception (VGGNet, GANs, ResNet, DenseNet, U-Net, DeepFace), AlphaGo, Capsulenet, GNNs, etc [8]. DL (deep learning) algorithms are employed in healthcare sector to advocate the adoption of advantageous healthcare plans to offer a preferred patient treatment service. In many ways, DL can be effectively used in healthcare applications such as radiology imaging (MRI, CT scans, etc). This highlights the need for deep learning in analysis of huge scanned image data sets of human organs or body parts. DL enables healthcare professionals to understand the concealed features in the big data for successful forecasting of diseases and reinforcement of appropriate healthcare systems. Recently, medical image systems have incorporated DL-based methods to improve healthcare applications, such as automated devices that assemble medical information, anticipate illness diagnoses, and conduct real-time patient monitoring. Despite extensive research in big data and DL, the healthcare industry has made limited progress in DL-based solutions for large MI data examination. Understanding the DL methods used in medical image analysis to handle medical data is therefore very crucial.

IV. DL-BASED MI APPLICATIONS

DL is gaining popularity for its use in massive healthcare data [2]. Hospitals and radiology departments create a large number of medical images, resulting in big medical image archives. An automated MI system is required to efficiently deal with this large amount of data. The primary goal of adopting DL in MI is to assist radiologists and doctors in more effectively handling diagnostic and therapeutic processes. The use of DL as a pattern identification technique is also becoming an important aspect of MI. [2]. DL investigations can be performed on medical images obtained from several human body sections or organs, including the brain, neuro, retinal, breast, heart, stomach, bone, and musculoskeletal regions. Fig. 3b depicts several human organs/parts and disorders connected with DL applications in MI [3]. Deep learning networks can be successfully applied to big data for information investigation, knowledge operation, and knowledge-based forecasting of diseases. Many variables contribute to DL's incredible success, including (i) the availability of huge data, (ii) greater computing power with ultramodern central processing units (CPUs) and graphics processing units (GPUs), and (iii) the invention of an improved technique to train DNNs. (iv) the availability of open-source deep learning libraries such as Cognitive Toolkit (CNTK), Caffe, Torch, TensorFlow, and Theano [2]. DL is ideal for medical big data since it can automatically recognize lesions, provide differential diagnoses, generate preliminary radiological reports, etc [13]. X-ray, ultrasound, PET, CT, MRI, and OCT are used for image segmentation that is based on DL for MI [9]. Segmentation of the breast tissue was successful using DL. GAN was utilized for the segmentation of aggressive prostate cancer tissues [14]. CNNs are applied for the segmentation of brain tumor MRI images [Fig. 3c] [9, 15].

TABLE I. A LIST OF DEEP LEARNING ARCHITECTURES FOR MEDICAL IMAGING APPLICATIONS.

MI Modality	DL Method	Dataset	Applications
CT	CNN	Image classification	Diagnosis and classification of pulmonary nodules.
CT	Deep CNN	Batch-based algorithms	Patterns of Interstitial Lung Dis-ease (IDL).
Neuroimaging	10-layer CNN	Batch normalization, dropouts and PReLU techniques.	Identify Alcohol Use Disorder (AUD).
fMRI	Two-stage CNN	Frequency Normalized Sampling Method	Autism Spectrum Disorder (ASD) recognition.
MRI	CNN	OASIS	Alzheimer's disease recognition.
Endoscopy	CNN	VGG-16 model	Cancer (EGC) & isolating endoscopic images into EGC & non-EGC.
OCT	SURF and RANSAC	Longitudinal 3D retinal images	Pre-processing for image projection & applying enrichment filters.
Feature extraction	Autoencoder & Decoder network	Log-Likelihood	Examining skin lesion (SL) segmentation.
Dental X-rays	U-Net	Electron microscopic stacks	Caries detection.
CT	DLA framework	Supervised MSS U-Net and 3DU	Diagnosis of kidney tumor & automatic segmentation of kidney defects.
Fundus	13 layers CNN	Image classification	Diabetic retinopathy analysis
X-Ray	GAN	Deep transfer training	Detect COVID-19 using CXR images.
CT	FCNet classifier	GoogLeNet	Classification of liver lesion (LL).
MG	R-CNN	DREAM CHALLENGE	Recognition of prostate cancer in breast cancer metastasis (BCM).

Table 1 lists different MI modalities, DL architectures, dataset types, and medical applications [9]. DL architectures in MI have both advantages and disadvantages. Due to weight sharing, CNNs have reduced network complexity [2]. CNN image resolution performance is significantly superior due to improved representation capabilities [16]. Some rotation or tilt in images makes CNN analysis hard [2, 17]. RNNs are used to store information and manage sequential data of arbitrary length via feedback links [2, 18]. Training RNNs is difficult, and the vanishing gradient problem arises when utilizing RNNs [2, 19]. Due to restrictions on node connections, RBMs are quicker than regular BMs and more efficient in encoding [2, 20]. The energy gradient function of the RBM is difficult to compute, making training challenging. The algorithm employed in RBMs is not well known [2, 20]. GANs may provide the most detailed images. Because GANs are unsupervised, there is no cost for labeling [2, 21]. GANs are challenging to train for accuracy testing and to generate results from text and speech [2, 22]. Although DL works well with MI big data, there are a few issues that must be addressed, such as the large size of the dataset (significant quantity of training data), sharing of sensitive data (data security), and difficulty to interpret DL produced MI data [2].

V. Conclusions and Future Perspectives

This mini-review provides a brief introduction to deep learning in the field of medical imaging, focusing on certain commonly used DL models and their applications in the medical field. DL's ability to extract the characteristics automatically and its skill in processing large amounts of medical image data are the reasons for its widespread use in medical imaging. To fully utilize DL in the medical industry, it is critical to take everything seriously. This study examines the potential of certain popular DL methods for analysis of MI data. DL performance is determined by its architecture and the number of layers. One obvious step forward as we consider future possibilities is to integrate the MI with other clinical data (blood tests, medications, genomics, and non-imaging ECG data). It creates global infrastructure and new privacy and security regulations—between hospitals and academic research institutes. In the future, DL applications in MI will enable unsupervised investigations, thus accelerating novel medical discoveries.

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