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Biomedical Image Segmentation by Deep Learning Methods

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Abstract
Deep learning methods have been employed to predict and analyse various application in medical imaging. Deep Learning technology is a computational algorithm that learns by itself to demonstrate a desired behaviours. Neural network processes the input neurons according to the corresponding types of networks based on algorithm provided and passes it to the hidden layer. Finally, it outputs the result through output layer. Deep learning algorithms tend to be more useful in different applications. It plays important role in biomedical image segmentations such as identifying skin cancer, lung cancer, brain tumour, skin psoriasis, etc. Deep learning includes algorithms like Convolutional Neural Network (CNN), Restricted Boltzmann Machine (RBM), Generative Adversarial Network (GAN), Recurrent Neural Network (RNN), U-Net, V-net, Fully Convolutional Attention Network (FCANET), Docker- powered based deep learning, ResNet18, ResNet50, SqueezeNet and DenseNet-121 which processes on medical images and helps in identifying the defect in earlier stage by helping the physician to start the treatment process. This paper is about the review of deep learning algorithms using

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medical image segmentation. Future implementations can be performed through additional feature for the existing algorithm with better performance.

***Keywords*:** Deep learning, convolution neural network, image processing, image segmentation

6.1 Introduction

Medical image processing is the crucial part of healthcare for performing variety of diagnostic steps. The diagnostic steps hold formation of visual and functional representations of human body and internal organs for medical analysis. This helps in determining the future need for image analysis in medical domain [1]. It includes different kinds of images like X-ray, Magnetic Resonance Imaging (MRI) [6], Computed Tomography (CT), Molecular Imaging, Ultrasound Imaging (US), and Mammography. These types of clinical images are needed for examine several human organs [2, 52]. Medical imaging consists of two components: 1) Image formation and image reconstruction: Image formation involves constructing two dimensional images for a three-dimensional object and reconstruction [3] involves set of iterative algorithms which forms two dimensional and three-dimensional images from the projected data of an object. 2) Image processing and analysis involves enhancing of images through noise removal techniques and feature extraction for image recognition or analysis.

Due to vast availability of advancement in technology, image acquisition is easier and the cost for generating huge volumes of high resolution images is very less. This, in turn, lead in the advancement in the field of biomedical image processing algorithms and this facilitated for the evolution of computerized image analysis or interpretation of algorithms to select valuable knowledge [18, 19, 21, 22]. Segmentation is the fundamental step in automated analysis which isolates the images and provides semantic information for the given problem. The regions in the images have semantic aspects intensive of grey level [4], color, and texture. The establishment of similar levels of image texture or layer thickness [5] can be done by the process of clear segmentation. Instance segmentation is done by isolating the objects of same class, while in semantic segmentation objects the same classes are not separated. Image segmentation procedures can be classified into three main groups: 1) Manual Segmentation (MS), 2) Semi-Automatic Segmentation, and 3) Fully Automatic Segmentation. MS technique [6] needs subject experts to resolve Region of Interest (ROI) and obtain the actual bound that covering ROI to obtain each pixels exactly. MS technique acts as the basis for semi-automatic segmentation and fully automatic segmentation. This MS technique is attainable for only smaller image datasets. It results in wear boundaries for high resolution images with slight variations in ROI, in turn, results in large number of errors. Another drawback of this technique is it requires subject experts' advice and experience which results in variations on subject knowledge [7].

Semi-automatic segmentation results in comprises of limited usage of user interactions with computerized algorithms to outcome definite segmentation results [8]. This results in near introduction of ROI which splits the image completely. It also consists of manual checking and selection of region boundaries to decrease the segmentation error. The examples of semi-automatic segmentation techniques contain 1) seeded region growing (SRG) algorithm, 2) level set based active contour model, and 3) localized region-based active contour technique. SGI algorithm combines the neighborhood pixels common intensity based on user provided initial seed point. The advantage of level set based active contour model does not require prior knowledge about shape and ROI initial locations [9]. This method starts based on the introductory boundary shapes provided by contours and manages by shrinking or expansion operation which depends on latent level of a function. The localized region based active contour explains about the foreground [10] and background of images using small local regions with the parameters along with the management of heterogeneous textures.

In "Evaluation of semi-automatic segmentation methods for persistent ground glass nodules on thin-section CT scans", Young Jae Kim *et al.* [10] proposed methods for performing the thin segmentation on lung CT scan images [47]. Five methods of semi-automatic segmentation were applied such as level-set–based active contour model, localized region-based active contour model, seeded region growing, K-means clustering, and fuzzy C-means clustering. It was found that the level-set–based active contour model resulted best with the approval of two radiologists for identifying the diagnosis and prognosis of lung cancer, when compared with other methods.

G. Wang explained about the viewpoint on deep learning in "A Perspective on Deep Imaging" [3]. The authors processed National Lung Screening Trail [40] for reconstruction of lung images. They tried with three CT images and obtained three results such as transforming low quality image into a good quality, low quality sinogram to better quality sinogram, and images with MGH Radiology chest CT datasets resulting in deep learning methods to obtain images faster rate. Figure 6.1 shows the CT image reconstruction.

The complete automatic segmentation techniques require no user communication. The maximum procedures are relaying on supervised learning methods that requires training data, e.g. deep neural networks, atlas based segmentation and shape models. In unsupervised learning approaches images are characterized through by MS. The challenges are dealing medical images which contain modifications in size, shape, texture and certain cases color of ROI among patients. In real applications noise or lack of consistency in source data results in wide variation [11]. Because of these variations the machine learning approaches sometimes does not suits for real world applications, which limits the usage of global applicability. Machine learning approaches which have been used for few engineering methods like Support Vector Machine (SVM) and Neural Networks (NN) are prolonged in the case of handling raw data and thus does not provide enough information at few cases. On the other hand, deep learning methods are potential enough to handle raw form of data and have been implemented effectively in sematic segmentation of images which had enormous application in biomedical image segmentation. The usage of deep learning methods processed in faster central processing units (CPUs) and graphical processing units (GPUs), in turn, reduces the execution time and can access larger datasets [4]. Further, the detailed explanation about the machine learning approaches along with image segmentation, deep learning approaches with image segmentation, [13] architecture for deep learning, different methods for implementing machine learning and deep learning architecture along with the performance measures used for segmenting medical images are explained in following sections.

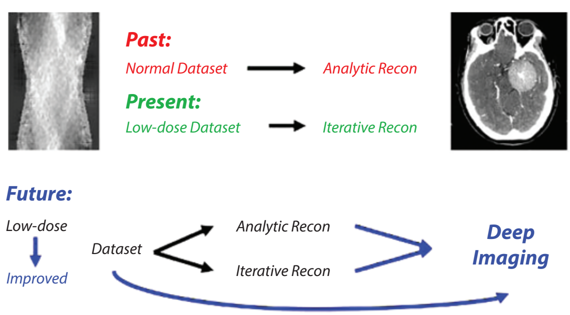

Figure 6.1 CT image reconstruction (past, present, and future) [3].

6.2 Overview of Deep Learning Algorithms

The most common uses of image segmentation approach by machine learning is to analyze ROI such as the region detected is disease or not. The step begins with basic process called pre-processing which removes the noise with the help of filter to enhance the contrast of the image. Further, it is followed by image segmentation techniques such as thresholding, approaches based on cluster, and edge-dependent segmentation. Once it is done, feature extraction process is done based on information regarding color, texture, contrast, and size from ROI. Principal Component Analysis (PCA) or Statistical Analysis method has been implemented for extracting important features, in order to use as input for the ML classifier like SVM and NN [64]. Figures 6.2(a) and 6.2(b) detail the ML classifier to detect the optimal segmentation (bisection of images) process and can classify any unknown data [62, 63]. The challenges in pre-processing involve in determining the appropriate requirements for the raw images, identification of similar features, feature vector's length, and the type of classifier among them [14].

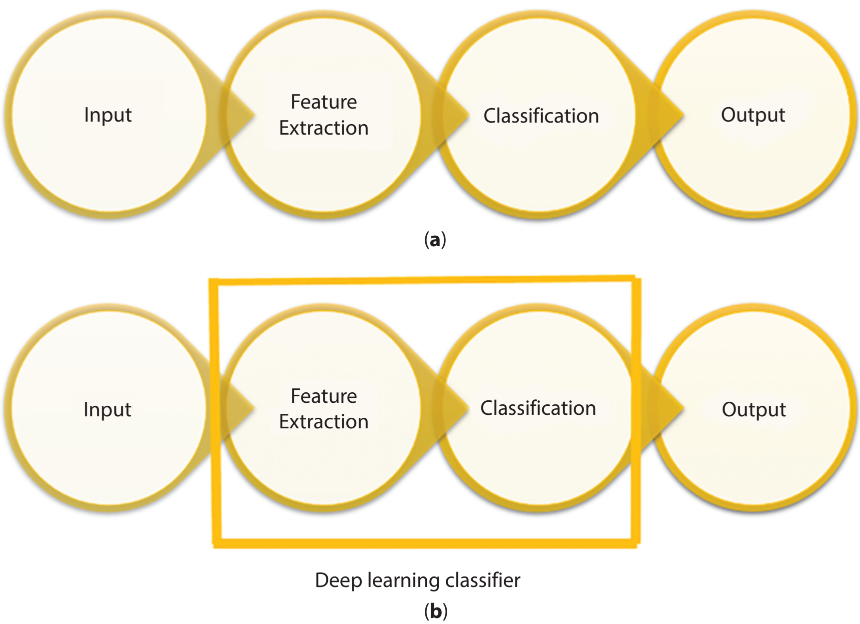

Figure 6.2 (a) Classic machine learning algorithm, (b) Deep learning algorithm.

6.2.1 Deep Learning Classifier (DLC)

It processes images without the requirement of pre-processing, segmentation, and extracting the features. Due to the limit of input size, deep learning approaches require image resize while other methods may require contrast enhancement and intensity normalization in order to avoid augmentation technique. DLC avoid errors during feature vector or incorrect segmentation and results in higher classification accuracy. DLC [4] has overcome the traditional image processing features by resulting optimal results with the help of neural network architecture. As shown in Figure 6.3, the DLC has numerous hidden layers where mathematical operations are performed comparative to ML approaches, which makes DLC more comprehensive.

ML classifier takes input as feature vector and process object class as output. But, DLC inputs image and processes the output as object class. Convolutional Neural Network (CNN) [4] is considered as the enhancement of deep learning models and CNN contains more layers than ANN [13]. CNN [54] is considered to be the representational learning in which the initial or first layer transfers the input data from the past layer to a new representation layer at greater levels of consideration. This CNN model helps to master both local and inter-relationships of entire data in a graded manner. The process of data transmission into representing as each layer of deep learning model is called non-linear function [4] as shown in Figure 6.3. The first layer representation will extract feature from given image such as existence or non-existence of edges in particular order and its location in the corresponding image [14]. The second layer identifies pattern by observing the location of edges and avoid negligible differences in the pattern. The third layer collaborates these patterns into larger combination of similar objects which are interrelated fragments and then send to the succeeding layers to identify objects with the help of these combinations. This method leads to an unexpected success of deep learning in the artificial intelligence [13].

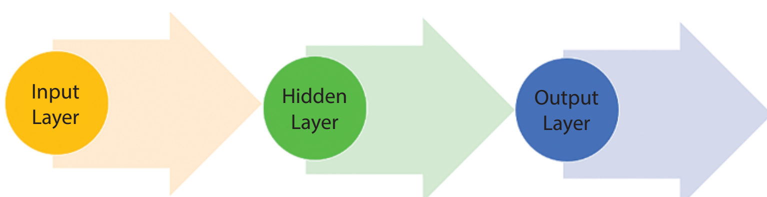

Figure 6.3 Traditional neural network.

6.2.2 Deep Learning Architecture

In deep learning architecture, CNN is frequently used which has similar property of Fully Convolutional Neural Network (FCNN). CNN takes an image as input and results a three-dimensional patterns of neurons comprising low region of preceding layer rather than displaying whole layer. As shown in Figure 6.4, the CNN includes layers of convolutional layer, rectified linear unit (ReLU) [56] which functions as non-linear activation layer, fully connected layer, or pooling layer. The convolutional layer performs convolution operation among the pixels of input image and performs filtering operations to attain the features. ReLU performs non-linear activation layer proceeds as the function f(x) = max (0, 1) as input values to increase the non-linearity along with betterment of training speed. The reduction in spatial dimensionality in image is due to pooling layer which inputs the images and improves the computational cost and avoid overfitting on neighboring pixels. The last layer in CNN is called as a fully connected layer. It ensures that the neurons in the current layer are connected to the previous layer [14].

CNN is often used for classification problem and when it is used for semantic segmentation the input image is sub divided as smaller patterns of same size. It classifies the central pixel and it descends to identify the next pixel. This method is less effective as it overlaps the features results in fall of spatial information by not using the same features. This is forwarded

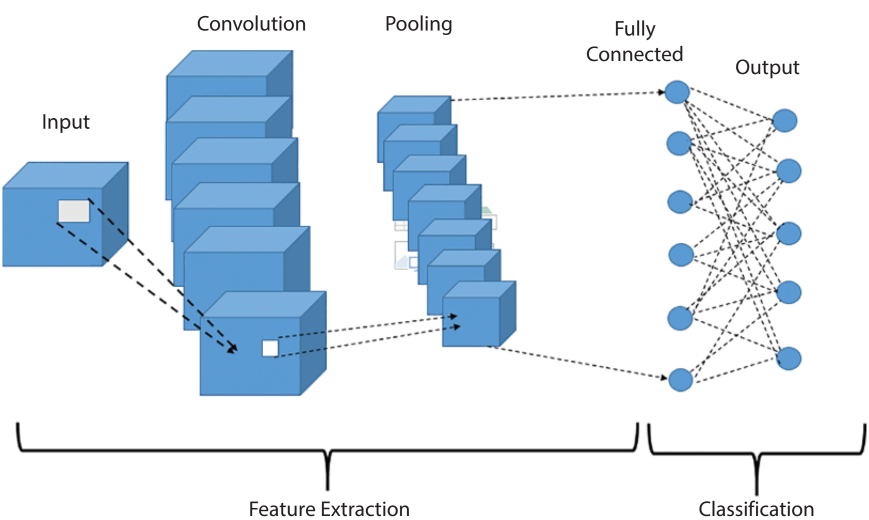

Figure 6.4 Convolutional Neural Network.

to the final layers of fully connected network. To avoid such problems, a transposed convolutional layer is proposed which processes on low-resolution features by up-sampling to regain initial spatial dimensions along with sematic segmentation. Generally, deep neural networks are trained by back propagation algorithm along with an optimization algorithm like gradient descent. In gradient descent algorithm, the gradient loss function determines the error and the weights are updated for minimizing the value of loss function [12].

Roth HR *et al.* proposed, in "Deep Learning and its Application to Medical Image Segmentation" [11], semantic image segmentation which is considered to be the challenging task in medical domain. They built a 3D Fully Convolutional Network which processes with the help of 3D medical images and produce automatic image segmentation. The dataset was obtained from gastric cancer patients. Future implementation can be done by detecting the shape of the segmented anatomy.

"Severity Grading of Psoriatic Plaques using Deep CNN based Multi-Task Learning" was proposed by Anabik Pal *et al.* who worked with Psoriasis skin disease dataset. Figure 6.5 shows image of skin Psoriasis of different areas in human body. It has been taken from 80 patients (done for research purpose, not public data or private data). They have implemented the psoriasis dataset with STL (Single-Task Learning) and MTL (Multi-Task Learning). MTL indicates that when a feature masters a distinct task, it will help others to learn the task prominent. The proposed MTL consists of five layers which help to identify the area involved and severity parameter of the skin. It resulted in better results in MTL than STL [2].

Figure 6.5 Psoriasis images [2].

6.3 Other Deep Learning Architecture

6.3.1 Restricted Boltzmann Machine (RBM)

RBM are neural networks that are formed from basis of energy-based models (EBM), as shown in Figure 6.6. They cipher the dependence among the variables by accrediting the scalar energy to the variables that are present separately. Interpretation or forecasting is done by detected variables to determine the balance value in order to decrease the energy. The energy function enables to learn the correct values for getting the balanced values. The higher values detect the incorrect values. The loss function obtained is minimum which indicates the proportion of the prevalence of accessible energy function. The RBM comprises of an input layer, hidden layer, and bias, and it does not contain output layer. While training the RBM, energy functions are decreased by providing the network parameters as input for the RBM. The neurons in each state can be detected as active (1) or inactive (0) based on the time values in each state. Deep Layer Network is obtained by arranging the layers of RBM. So, the layers reach out first and second layers. The inner layers contain guidance (directions) and first two higher layers are with non-guidance (undirected). On the contrary to RBM, Deep Boltzmann Machine includes order less communication, and they can be managed for unpredictability in case of strident inputs [57, 58].

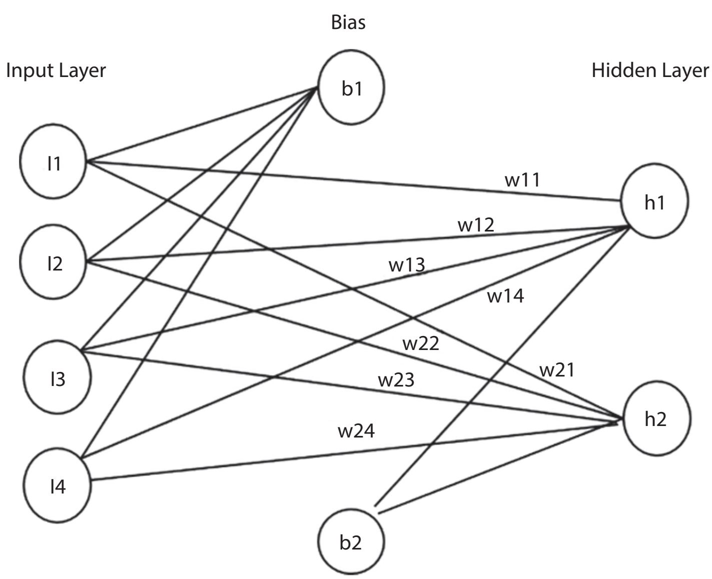

Figure 6.6 Restricted Boltzmann Machine.

6.3.2 Deep Learning Architecture Containing Autoencoders

In deep learning architecture, autoencoders are considered to be the unsupervised algorithms in which it consists of input layer fed as latent space by providing backpropagation algorithm as target values. The autoencoder comprises of two portions encoder and decoder. The encoder part shortens the input into latent space representation and decoder regenerates the input obtained from the latent space. This process defines confining and it converts the hidden layer into poor dimensions, which leaves the network as under complete by providing outstanding feature from the training data. It can also be achieved when the neurons are kept in inactive state. The architecture of autoencoder consists of images as input which converts into lower dimensions so that the autoencoders are trained to gain information from the images.

Major threat lies in hidden layers, as more number of nodes is present in hidden layers when compared with the input layers of the autoencoders. This results in situation where the number of nodes in input layer and output layer becomes equal leading to the exposure of network null or identity function. To avoid such situations, usage of denoising autoencoder in which 30%–60% of random inputs are provided as zeros. Those values that reduced to zeros depend on the size of the data and nodes in the network. While calculating the loss function, to avoid the risk of null function, output is cross checked with the original input. The applications of autoencoders are very less due to its latent representation which does not allow for uniform model presentation. To overcome these drawbacks of autoencoders, variational autoencoders are introduced. They produce two vectors as output instead of one. The two vectors are one that is to calculate the mean value and the other that is to calculate the standard deviation value. These are considered

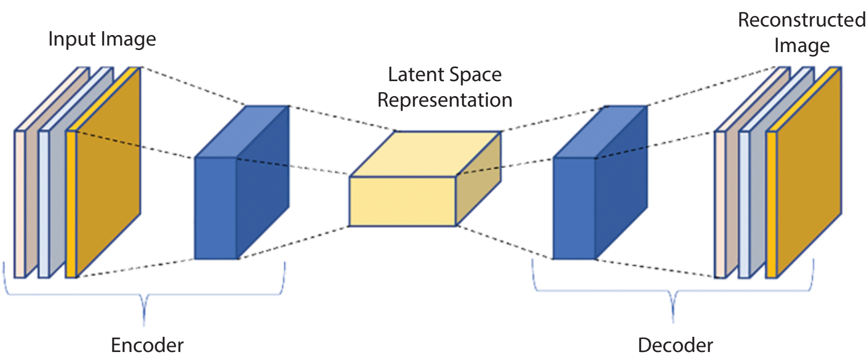

Figure 6.7 Autoencoder architecture with vector and image inputs [1].

to be the attributes acting for random variables. This makes the decoder to perform its operation accurately to decode the encoded values while training even the variations is smaller. Thus, the autoencoder allows for interpolation and sampling by designing latent space representation. Deep learning architecture of autoencoders with vector and image inputs is shown in Figure 6.7.

6.3.3 Sparse Coding Deep Learning Architecture

It belongs to unsupervised learning algorithm which represents the input data by determining the complete sets of basis vectors. This indicates that the dimension of the latent representation is more than the input data. The challenge is to identify the combinations between the inputs. The overcomplete network represents the insufficient situation for performing during degradation in the network [14]. Identification of similar descriptors and conquering the corresponding properties of the given image is a complex task.

6.3.4 Generative Adversarial Network (GAN)

GAN model builds data to perform transform function which includes generator implemented in the network. It helps to consider random variable as input and once trained it produces the resultant distribution. Different layers are trained in a way to differentiate the original data and developed data. These two layers act as competitors in which the initial layers try to maximize the regulation error among the original and developed date. While the preceding layer try to minimize the same error. In the end, all these layers improve the training process. "Skin Lesion Segmentation via Generative Adversarial Networks with Dual Discriminators" proposed Generative Adversarial Networks on the public International Skin Imaging Collaboration (ISIC) Skin lesion dataset which resulted in superior method are obtained [58].

6.3.5 Recurrent Neural Network (RNN)

RNN are used in cases when input size cannot be determined in advance in which the network works in serial manner. This is impacted by the network because the serial input differs from other inputs as it affects the nearby values. The relationship has to be noticed by the network and the RNN results obtained are based on the past learning and present input variables. The past input data is on the network and it is stored in hidden state vector. Thus, we can obtain different output from the same input based on the past input available in the series. This network becomes periodic when it transforms recurrently which results in the formation of fixed size output vector. The updating of hidden layer is done for each input values and depth of the network can be modified by adding hidden layers. It can also be done by addition of non-linear hidden layers in between the layers or vice versa.

There are numerous approaches for applications of deep learning techniques for image segmentation. Initially, training process is done on the neural network from the basic which gathers the requirement or availability of the labeled data. It is ensured whether it is time saving for building the network. Secondly, model is fitted in the neural network such as already trained CNN is utilized which classifies approximately 1 million of image consisting high resolution present in ImageNet Large Scale Visual Recognition Challenge. The target is to remove the low feature last layers and to be replaced with new task specific. Millions of images are present and low level features are gained from initial layers are grouped along with the task specific features obtained from the last layers to perform classification among the images. This is considered to be the advantage of less time consumption to achieve smaller number of weights [15]. The researchers used CNN along with MTL (Multi-task Learning) to make the layers to share multiple tasks [35–37]. The major advantage of MTL is the need of less memory and increases the overall accuracy rate.

Thirdly, it is to implement classic classifier models like support vector machines to extract features from the input image and passing those to train for classification. This removes the time spent for extraction and thus removes the more number of absolute (categorical) data. CNN method was developed for biomedical image segmentation and volumetric medical image segmentation. There are two types of convolutional network, U-Net [16] and V-Net [17]. A type of FCN [50] (U-Net) provides expansion and contraction path in the network. The contraction path consists of subsequent convolutional layer and max pool layer. This layer acquires the features by reducing the size of feature map. Up conversion operation called as extraction is done in order to regain the segmentation map size with some loss of information. This information is shared from the contraction layer to extraction layer. This enables the signals to move from one network to next. The result is gained by output vector with the target classes. In volumetric network (V-Net) [17], it functions same as U-Net. V-Net is described as compression and decompression measure. Multiple stages are present in compression part each stage consists of 1 to 3 layers. Volumetric data voxels (a voxel is a unit of graphic information that defines a point in three-dimensional space) help in gaining knowledge about residual function. The compression part cut down the resolution identical to the pooling layer. The ample information for the volumetric segmentation is identified by expanding the spatial features. The size of the input is increased and residual function is obtained during the compression part of network. This process is called deconvolution.

Intisar Rizwan *et al.* who proposed "Deep Learning Approached to Biomedical Image Segmentation" explained about various features which plays important role in obtained the best result. Their work explains the solution for the certain given problems. It also implicates when implementing DLC, and it requires huge data, resulting in storage of enormous memory. This is considered to be the challenging task. In case of medical data, image data is not easily available. It was concluded by mentioning open datasets can be made available for medical image [1].

Performance Metric

The competency image segmentation method has been verified using traditional and familiar methods and it has been analysed by the various metrics and results are compared with other methods. Identification of correct method relies on the important metrics and factors that suit the exact system. While calculating the metrics, few things have to be considered such as complexity, accuracy, prediction, and many factors in Equations (6.1) to (6.5). The performance metrics are listed in Table 6.1.

Accuracy

It is defined as the ratio of correctly predicted pixels in image to total number of image pixels. It is used to classify the correct pixels present in the image.

$$Accuracy = \frac{Correctly\ Predicted\ Pixels}{Total\ number\ of\ \ Image\ Pixels} = \frac{TT + TF}{TT + FT + FF + TF} \tag{6.1}$$

Table 6.1 Definition of the abbreviations.

Category	Predicted disease	Predicted no disease
Actual disease	True True (TT)	False False (FF)
Actual no disease	False True (FT)	True False (TF)

Precision

It is defined as fraction of correctly predicted disease (pixels) to the total number of predicted disease (pixels). It is used to measure the performance metric.

$$Precision = \frac{Correctly\ Predicted\ Disease\ Pixels}{Total\ number\ of\ \ Predicted\ Disease\ Pixels} = \frac{TT}{TT + FT} \tag{6.2}$$

Recall

It is defined as fraction of correctly predicted disease (pixels) to the total number of actual disease (pixels).

$$Recall = \frac{Correctly\ Predicted\ Disease\ Pixels}{Total\ number\ of\ \ Actual\ Disease\ Pixels} = \frac{TT}{TT + FF} \tag{6.3}$$

F1 Measure

It is also called as boundary F1. Precision and recall are considered as important factor for predicting the results. It also helps in determining the mean of precision and recall used for matching boundaries between predicted segmentation and ground truth segmentation.

$$F1measure = \frac{PresPrecision \times Recall}{PresPrecision + Recall} \tag{6.4}$$

Jaccard Similarity Index (JSI)

It performs Intersection Over Union (IoU) and is calculated as the ratio of the overlap between the predicted segment and the ground truth segment to the area of union between the predicted segment and ground truth segment.

$$JSI = \frac{SGround\ Truth \cap SAutomated}{SGround\ Truth \cup SAutomate} = \frac{TT}{TF + FT + FF} \tag{6.5}$$

S – Segmentation

6.4 Biomedical Image Segmentation

There are diverse methods for biomedical image reliant on imaging techniques. Biomedical imaging techniques are explained further. This method helps in prior prediction about the diseases and other related information which promotes earlier detection of diseases. Skin covers the entire body and it needs immediate treatment if affected. We try to cover all medical defects and to improve the ways for identifying the defects in human body with the deep learning algorithms. Numerous medical illnesses occur and corresponding treatment measures has to be done with the help of images.

Chenga, *et al.* in "Fully convolutional attention network for biomedical image segmentation" proposed Fully Convolutional Attention Network (FCANET) [60]. They used lung x-ray image dataset from "The Chest X-ray Collection", the Kaggle 2018 dataset, and the Herlev dataset. The result obtained was able to obtain certain features and future implementation can be done which results in better performance than FCANNET. Figure 6.8 shows chest x-ray images.

In "Kwon, *et al.* Docker-powered Deep Learning for Biomedical Image Segmentation" Xinglong Wu *et al.* [61] proposed Docker-powered–based deep learning which inputs mouse brain [24–28, 30–34] image for segmentation resulting in accuracy of about 0.96. This helps in similar segmentation of human brain tumor using MRI. The dataset used is SBEM dataset (available from https://github.com/CRBS/cdeep3m/wiki/data/datasetone.zip).

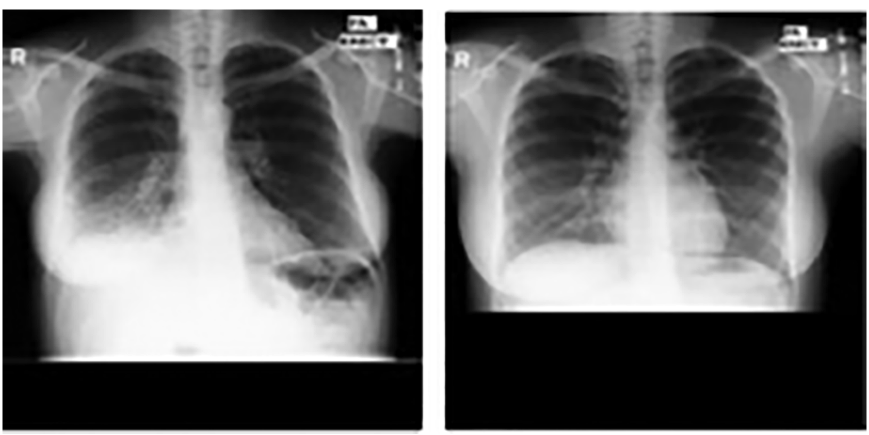

Figure 6.8 Image of chest x-ray [60].

6.4.1 Clinical Images

Clinical images of skin in case of injury such as skin burn, allergy, irritation, and rashes, rarely skin cancer which cannot be predicted in early stages. At that situation, clinical images play a major role in the skin treatment. With the help of clinical images, the treatment process can be planned and treated in efficient way.

Sumarno Adi Subrata *et al.* in "Improving clinical outcomes of diabetic foot ulcers by the 3-month self- and family management support programs in Indonesia: A randomized controlled trial study" performed a self-care of diabetic foot ulcer patients at home for 90 days. This results in 0.05 for hypothesis testing. This shows that there is steady improvement in patient's diabetic foot ulcer [59].

6.4.2 X-Ray Imaging

X-ray images are commonly used problem detection techniques in case damage occurs in bones, fractures such as bone dislocations, etc. Medical x-ray images are available online and machine learning models are implemented to detect and cure the illness in earlier stage [1]. Figure 6.9 shows x-ray of chest with different thoracic disease. X-ray images help in identifying COVID-19 in humans. The researchers taken 5,000 radiography images which were available in public dataset used deep learning models such as ResNet18, ResNet50, SqueezeNet, and DenseNet-121. It resulted with sensitivity of about 98% (± 3%) [55].

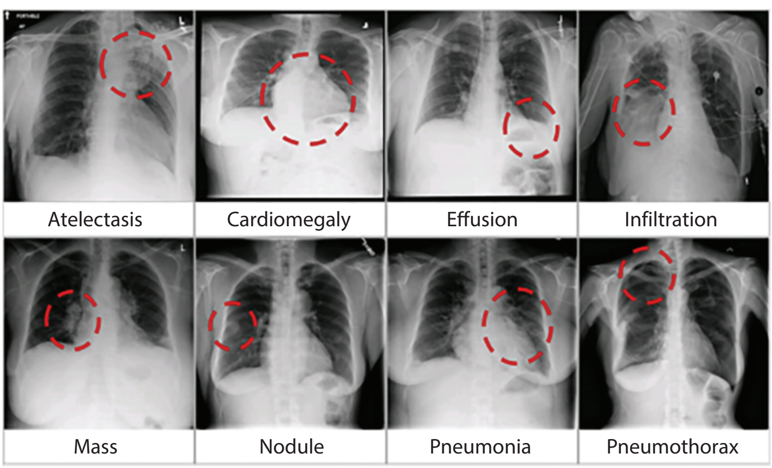

Figure 6.9 Regular thoracic disease identified in chest x-rays [23].

6.4.3 Computed Tomography (CT)

It is referred as CT images [3]. It helps to obtain the detailed cross-sectional images of human internal organs, blood vessels, tissues, and bones. These cross-sectional images are obtained by passing x-rays to the patient. Traditionally, the images are captured in the axial or transverse plane and perpendicular to the corporeal long axis. The images obtained are called as slice is reformed into many planes and it forms 3D images [38, 39, 44–46, 48, 49]. CT images are used to detect cancer based on the existence of tumor along with the size. Two CT scan of Lung was obtained for the evaluating the semi-automatic segmentation of Ground Glass Nodules (GGNs) on thin section of CT scans [10]. To categorize the low and high resolution image, deconvolution methods were performed on CT images [53]. The CT images helps in analyzing COVID 19 cases such as identifying positive and negative with accuracy of 0.994 [54].

6.4.4 Magnetic Resonance Imaging (MRI)

MRI is image processing technique in which it captures the physiological processes, tissues, and organs of the humans. It is used to detect crack in the bones and knee joints. Any damage to the bones can be detected by MRI [6]. It is used to distinguish between the white matter and grey matter in the bone. It functions similar to CT scan with additional feature in which it uses ionized radiation of X-rays. Alexander Selvikvåg Lundervold *et al.* in "An overview of Deep Learning in medical imaging focusing on MRI" explain challenging methods for dealing with medical image analysis with the help of deep learning methods. They tried to explain much detailed about MRI processing in field of deep learning and segmentation of images using different methods by contributing to the research of medical images [51].

Işin *et al.* proposed [6] the "Review of MRI-based brain tumor image segmentation using deep learning methods". They proposed methods which help to identify the defect in brain and diagnosis the defect using automatic image segmentation technique. They take MRI of the brain tumor [29, 42] called BRAST dataset provided with review of the different methods for brain tumor image segmentation. For future implementation, CNN architecture can be along with Diffusion Tensor Imaging (DTI), Positron Emission Tomography (PET), and Magnetic Resonance Spectroscopy (MRS).

In "Deep learning for Corpus Callosum segmentation in brain magnetic resonance images", Henrique Schuindt [4], has implemented FCNN [41]

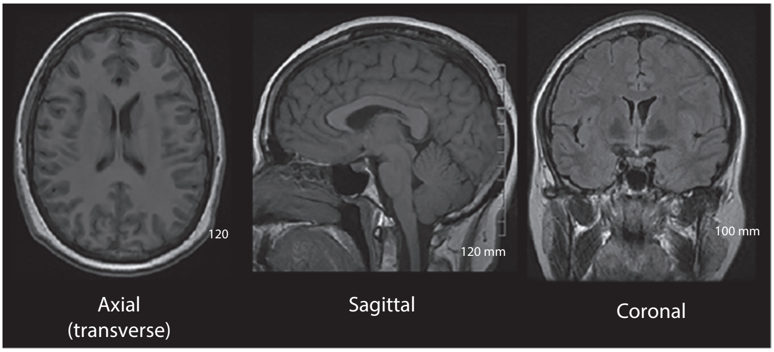

Figure 6.10 MRI of human brain [4].

with U-net [16] for the biomedical image segmentation. OASIS [42] and ABIDE were taken for the analysis which are in the form of MRI [43]. The result obtained was 95.10% accuracy. This can be further improved by using SegNet [42] with other segmentation networks. Figure 6.10 indicates MRI of human brain in three different views such as axial, sagittal, and coronal.

In "VoxResNet: Deep voxelwise residual networks for brain segmentation from 3D MR images" Hao Chen *et al.* [20] proposed a best network called VosRexNet which helped to solve the challenging task in the field of deep learning in 3D. This network helps to represent features dealing with tissues of the brain. The future enhancement can be done by adding some different levels in image such as MRI of brain along with VoxResNet.

6.4.5 Ultrasound Imaging (US)

This scanning technology uses high frequency sound waves for capturing human body parts. It is used to produce visual images of internal organs, blood flow, and tissues. It is used to check the fetus in the time of pregnancy. The main advantage of US is free from radiation and fast. It is used to scan the abdominal sections, vascular organs, and thyroid glands. It does not function well for scanning of aired organs such as lungs.

6.4.6 Optical Coherence Tomography (OCT)

This technique is based on low coherence light to gather the micrometer resolution of 2D and 3D images of tissues. OCT is mainly used for detecting any defects in the eye. It enables the diagnosis methods by providing the clear cross-sectional view of the retina. It helps the physician to view the retina clean cut layer by layer. OCT images of retina has been taken and processed with Gaussian Process and FCNN resulted in 0.01 human errors [57].

6.5 Conclusion

This chapter highlights the important feature related to deep learning in medical domain. It explains about how different medical defects in humans can be identified and processed. Apart from the physicians, deep learning methods help the physicians to detect the disease in earlier stage and help better treatment process. Human organs such as lungs, brain, and some more organs are identified with the cancer. Deep learning techniques help many more medical illnesses. Apart from that, many research questions are left unanswered. There comes the challenging task in domain of deep learning to obtain the results in shorter period of time. Today, we found that deep learning techniques play a major role such as skin cancer detection, lung cancer [40], skin diseases like psoriasis [2], brain cancer, and several defects related to brain [4]. In case of skin cancer, the result obtained was 99.99% for detecting skin cancer using deep learning techniques [52] so the physician can use the model for identifying the skin cancer at earlier stage. The deep learning techniques are proposed and it needs improvised algorithms with better performance. In future, deep learning algorithms can be implemented with better performance and improvised the techniques by combining multiple features.

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