International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 03, 2021

State-Of-The-Art Techniques On Medical Image Analysis Using Deep Learning

Dr.N.T. Renukadevi[1][0000-0002-0010-469X],Dr.K. Saraswathi[2][0000-0003-1746-0145], Mr.B. Anguraj[3]

[1]Assistant Professor, Department of CT-UG, Kongu Engineering Colleg
[2]Assistant Professor, Department of CT-UG, Kongu Engineering College
[3]B.Sc.(IS), Department of CT-UG, Kongu Engineering College

Email: [1]renuka.ctug@kongu.edu, [2]angurajbalasubramanium@gmail.com

Abstract. Digital imaging systems are currently being used in medical diagnosis and research. Digital images refer to the collection of pixels or picture elements that vary in terms of brightness and color. Medical images, specifically refers to the images generated from modalities like CT (Computerized Tomography), Ultrasound and MRI (Magnetic Res- onance Imaging). The main notion behind the study of medical images is to equip the quality of imaging. The recent innovations greatly dealt with recognition of images through Deep Learning methodologies which is the subset of Machine Learning. It learns automatically from the machine by practice without the need of programming explicitly. The medicinal imaging system includes five major processing steps such as acquisition, augmentation, segmentation, feature extrac- tion/retrieval and categorization. Through deep learning process, pre- diction can be done easily for analysis purpose. In this paper, the tech- nologically advanced methods that are being currently in use in medical imaging and the different phases of analysis process, structural design of deep learning, along with the challenges are discussed.

Keywords:Medical Image Analysis, Deep Learning, Artificial Neural Network, Recurrent Neural Network, Convolutional Neural Network

1. INTRODUCTION

Owing to the remarkable progress in image acquisition equipment's, the information to be stored is also vast enough, which poses challeng-es in investigation of images. This quick development in therapeutic images and modalities need wide-ranging efforts by physicians that is error prone and leads to huge dissimilarity among them. A classical medicinal imaging organization includes five significant processing methods such as Image acquisition, Quality enhancement, Segmenta- tion, feature extraction/retrieval and categorization. Alternative way is to use machine learning algorithms for habitual diagnosis process, but, those are not adequate to treat the multifaceted problems.[1]

A subcomponent of Machine Learning is Deep Learning (DL), imple- ments computing model in similar way the human brain works. It aids to extract intricate information from input images and not limited to this level, it also create new ones by self learning process. In addition to that, it makes prediction analysis so that the medical practitioners can make clinical decisions quickly.[2][3]

DL methods include neural networks, which consists of several layers of neurons possibly will be up to 1000, creating a chain of layers for feature demonstration. Having such a massive modeling capability, it can remember all probable mappings by unbeaten training with ade- quate level of data repository and formulate intellectual predictions. Hence, DL creates a key impact not only in computerized graphics and medical imaging but also in other domains like natural language pro- cessing, drug discovery, biometric recognition etc.,
The main objective of this review is to give detailed description of pro- cessing methods of medical images and DL based methodologies in current context and for future era.

2. METHODOLOGIES

2.1 Image acquisition:

Image acquisition is a process of retrieving images from hardware sources or capturing an image by camera. For medical imaging, the radiology images from acquisition modalities like X-Ray, Ultrasound, CT and MRI scans are of high resolution nowadays. Images obtained from different modalities are given as an input to Picture Archiving and Communication Systems (PACS). The acquisition process can be done in three ways, namely, discovery of the data and augmentation.[4] Dis- covery refers to collection and indexing of data for sharing. Image data augmentation is a method that is used to synthetically enlarge the volume of a training data repository by generating customized description of images. It appends value to pedestal data by accumulating infor- mation resulting from internal and peripheral sources.[5]The key issues here are to take account of how to extent the searching and how to put in the picture whether a dataset is appropriate for a specified machine learning chore.

2.2 Image Enhancement:

It is a process in which the resultant image is more appropriate when compared to the original one for a precise application. The tools of Im- age enhancement process are categorized as spatial domain and fre- quency domain. Spatial domain is the linear manipulations of pixels in an image. The processing resource required is very low due to the most effective computation. Point operations in spatial domain include elon- gation of disparate features, outliers clipping, histogram adjustment, and pseudo coloring, whereas, the point operations are trouble-free nonlinear procedures that are well recognized in image processing. Wavelet transformations are needed to decompose a picture to dissimi- lar frequency constituents are used in image processing applications also.[6]

2.3 Image Segmentation:

The objective of segmentation processes it to split the images to nu- merous segments with comparable features. The boundaries are detect- ed in an 2D or 3D image by this segmentation only. It can consign la- bels to all pixels so that the labels with similar characteristics can share their properties or attributes. The tedious task here is inconsistencies among the images. Hence, a considerable amount of concern is needed to improve the likelihood of strong segmentation. There are two basic types of segmentation. (i) Local segmentation, concentrates on specific region of an image and (ii) Global segmentation, which concentrates on the entire image with pixels. Recurrent Networks and CNN seems to dominate the medical image segmentation like brain MRI segmenta- tion, MRI cardiac segmentation, etc. [7]

International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 03, 2021

3. OVERVIEW OF DEEP LEARNING METHODS:

3.1 Artificial Neural Networks (ANN):

ANN is an information handing system which hold a bulky quantity of extremely interconnected neurons. These neurons toil collectively in a disseminated fashion to gain knowledge of the input descriptions, to synchronize interior processing, and to optimize its ultimate output. The architecture of a neuron is shown in Figure 1.

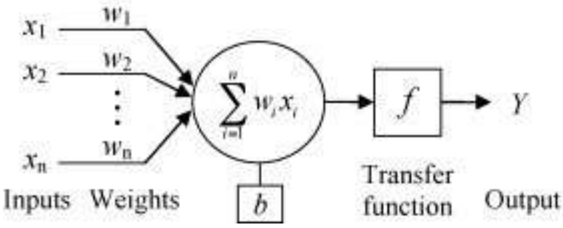

Fig. 1.Structural design of a neuron

In the above sketch, X {xi, i= {1, 2…, n)} characterize the key in to the neuron and Y characterize the output. Every input is multiplied by its weight W {wi, (i= {1, 2,…,n)} a bias b is linked with every piece of neuron and their total depart in the course of a transfer function f. Also, there are wide variety of transfer functions existing to compute the W weights and b Bias values like Linear, Sigmoid, Radial Basis Kernel, etc.[8]

ANN has been implemented in various applications of Computer- Aided Diagnosis (CAD) which shows the leading stream of computa- tional intellect in the field of medical imaging[3][4][9][10][11][12][8]. Artificial Neural Networks includes various types such as, Feed For- ward Networks (FFN), Back Propagation Networks (BPN), Recurrent Networks (RNN), etc.,[13][14].

In this paper, a study on computational intelligence with neural set of connections are being in use for image registration, segmentation and boundary recognition forpsychoanalysis, detection of diseases and di- agnosis is focused.

3.2 Convolution Neural Network (CNN):

CNN also called as Deep ANN works on the collection of neurons ar- ranged in consecutive layers to categorize images, identifying similar features and objects [15]. The initial layer is convolution layer, the core building block of a CNN, used to retrieve features from an image and it maintains the correlation among pixels by learning the input fea- tures of an image. It requires large volume of neurons according to the resolution of pixels in an image and filtration process will be done here. The next is pooling layer, which helps to reduce the dimensions of an image with sliding window approach. The third is fully connected lay- er, used to aggregate the information from previous layers and create final classification results. [3][16][17][18]

The major role of a CNN depends on its deep architecture since it ex- tracts a core of important features at various levels of generalization. But, training a CNN is cumbersome work since it requires huge volume of training data with labels which is tedious to obtain them in medical images. [19][20][21][22][26] Also, a deep CNN needs wide-ranging memory and computational facilities which is expensive and time- consuming, added to that, it becomes complicated by over fitting and convergence problems due to the frequent adjustments in the training parameters of the network. [23][24][25]. The architecture of CNN is given in Figure 2.

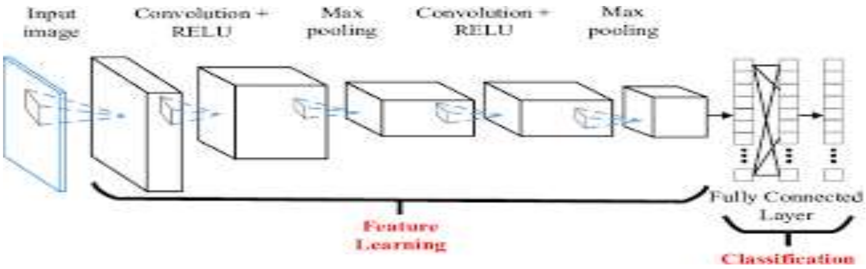

Fig. 2.CNN Architecture

3.3 Deep RNN:

RNN is a multi-layer ANN in which the relationship among nodes cre- ates a directed graph with a certain pattern of time-related transitions. It computes the inputs by using its own internal memory. It can predict the output which is a unique characteristic that is not available in other types of ANN and implements feedback process to compute the series of data. The feedback process helps to maintain the information per- manent and becomes useful for prediction.RNN consists of three layers, the first one is input layer, which has N input units. Those input values are fed as a series of vectors computed in a time period t like {xt-1, xt, xt+1…} where xt = (x1, x2,…, xN). The next layer is hidden layer which receives input from previous layer and connections are specified with weight matrix (WM). The hidden layer has M hidden units ht = (h1, h2,…, hM) and are linked to other unit on the basis of time t with persistent connections. The effective- ness and strength of the network depends on non-zero numbers in hid- den layer which helps to improve the performance [26]. The architec- ture of RNN is shown in figure 3.

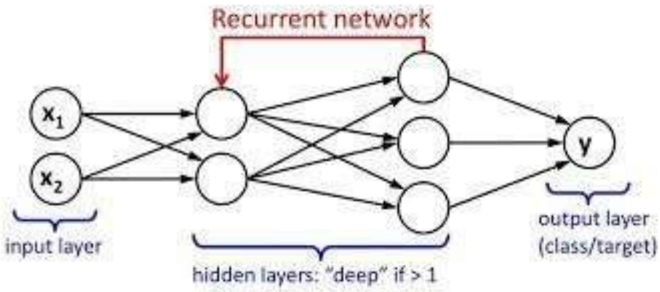

Fig. 3.RNN Architecture

The depth of RNN can be achieved when hidden layers can be added between input and hidden layers or added between hidden and output layers. [27]

4. APPLICATION OF DEEP LEARNING IN MEDICAL IMAGE ANALYSIS:

Massive computational power and high-tech challenging works on me- dicinal imaging is accomplished throughout deep learning. In recent years, image detection, segmentation and disease classification are highly involved with deep learning. CNN plays a vital role along with selected features among the different deep learning methods.

Clinical practice is improved through deep learning and its applications are budding day by day. Deep learning is applied in treatment of dis- ease in the form of radiation [28], Scanning of images through Positron Emission Tomography (PET) or MR Imaging to get detailed pictures of anatomy of body [29][30], in methods that extracts large volume of features from radiography [31][32], and in the field which combines diagnostic test with therapy in neurosurgical imaging[33][34].

Efficient methods involved in the analysis process in modern approach are used in deep learning. When deep learning is applied in healthcare industries, it provides preferable solutions to variety of problems like diagnosis of diseases, suggestions for personalized treatments etc... A good amount of data is generated through various methods of radiological imaging. Even though there are certain limitations in incorporating valuable data by deep learning model.

Gulshan et al. [30] focused on computerized detection of the diabetic retinopathy based on deep learning using two datasets and has shown great results like 97.5% sensitivity and 93.4% specificity on EyePACS- 1 data, and 96.1% sensitivity and 93.9% specificity on Messidor-1.

Cardiac imaging is usually done through MRI and CT scans. The labor- intensive classification of the Coronary Artery Calcium (CAC) scoring in cardiac scans is the uphill task and includes a vast quantity of en- deavor. Thus, this makes it to be a overwhelming chore for epidemic learning. Litjens et al. [35] confers various frameworks of deep learning which may perhaps be used for cardiovascular investigation.

The diagnosis of the disorders concerned with gastrointestinal tract which include diagnosis, prognosis and analysis of endoscopy, includ- ing wireless capsule endoscopy, tomography and MRI is mainly done by current imaging technologies. The accomplishment of this deep knowledge support come close to paved the way for the potential im- provement of software for automatic recognition of Gastro Intestinal Ang ectasia (GIA) from Endoscopy images.[36]

Renukadevi et al. [37] proposed an innovative method to categorize liver infection by means of Deep Belief Network with parameter fine- tuning. For liver disease classification, median filter preprocessing, fea- ture extraction is done. To lessen the dimensionality, extracted features have been reduced by means of Principal Component Analysis method. Followed by it, the image is organized by the implementation of DBN based Grasshopper Optimization Algorithm (GOA). It would choose the most favorable values for classification. As a final point, the CT scan images of liver are diagnosed.

5. RESEARCH ISSUES IN DEEP LEARNING:

Usage of deep knowledge in therapeutic imaging is quite challenging, since, as the size of network grow, the hundreds and thousands of con- straints and unexpected quantity of paths linking the nodes with set of connections makes the network as complicated one. In many of the deep learning network models, there are lacks of mathematical founda- tions which results in technical challenges. Some aspects of the medical field have been revolutionized by various methods of deep learning [38]. The foremost precondition to make use of deep learning is substantial amounts of preparation datasets. The excellence and estimation of deep learning classifiers depends deeply on value and quantity of the data [39]. Expansion of massive training dataset itself is sluggish works which have need of substantial work to done by the medical experts.

New-fangled procedures for training representation exclusive of reveal- ing the underlying data to the user are necessary. This is because of the reasons that privacy and data production are considered to be a com- mon requirement while dealing with medical data. Since expert annota- tors are limited, expenses to be made at outsized computational sources to increase the labeled training data are habitually worthwhile. Since, deep neural networks is mainly dependent on intricate hierarchical de- lineation of learning data to fabricate the forecast, and elucidating them is highly complicated. [3]

6. CONCLUSION:

In this paper, an overview of image acquisition, enhancement and seg- mentation is discussed. Then, the most popular network structures and their working nature applicable for medical imaging is summarized. The significance of deep learning methods in the analysis of medical image analysis are outlined. In the end, the most important issues relat- ed to deep learning-based explanation for medical imaging are focused. Despite the challenges correlated with the preamble of deep learning, the techniques generate enhanced consequences. Since, researchers and practitioners gain experience in the due course of time, it would not be problematic for them to decide on what kind of approach should be done to obtain the solutions which includes that the usage of deep learning techniques peer-to-peer node, and connecting it with other methodologies.

Despite the vast influence of deep learning in medical imaging, it is believed that awareness in the medicinal society could be used to rein- force the broad-spectrum of researchers and medical practitioners in the ground of computational medication.

7. REFERENCES:

[1]. T. K. Debashis Ganguly, Srabonti Chakraborty, Maricel Balitanas, "Medical Imaging: A Review," in *Security-Enriched Urban Computing and Smart Grid*, pp. 504–516 (2010).

[2]. C. GeertLitjensThijsKooiBabak, EhteshamiBejnordi, Arnaud Arindra AdiyosoSetio, FrancescoCiompi, MohsenGhafoorian, Jeroen A.W.M.van der Laak, Bramvan Ginneken, "A survey on deep learning in medical image analysis," *Elsevier*, vol. 42, pp. 60–88.

[3]. A. S. Lundervold and A. Lundervold, "An overview of deep learning in medical imaging focusing on MRI," *Z Med Phys*, vol. 29, no. 2, pp. 102–127, (2019).

[4]. M. I. Razzak, S. Naz, and A. Zaib, "Deep learning for medical image processing: Overview, challenges and the future," *Lect Notes Comput Vis Biomech*, vol. 26, pp. 323–350 (2018).

[5]. S. B. J. Blanc-talon, G. Gallo, W. Philips, and D. Hutchison, *for Intelligent*. (2015).

[6]. M. Rela, S. N. Rao, and P. R. Reddy, "Efficient image enhancement techniques applied on medical imaging-a state- of- the art survey," *Int J Recent Technol Eng*, vol. 7, no. 6, pp. 285–289, (2019).

[7]. Eine sanfte Einführung in Tiefes Lernen in der Medizinischen Bildverarbeitung, "A gentle introduction to deep learning in medical image processing," *Zeitschrift für Medizinische Phys Vol Issue 2, May 2019, Pages 86-101*, vol. 29, no. 2, pp. 86–101, (2019).

[8]. J. R. J.Jiang,P.Trundle, "Medical image analysis with artificial neural networks," *Comput Med Imaging Graph*, vol. 34, no. 8, pp. 617–631.

[9]. C. Z. Jun Ge, Berkman Sahiner, Lubomir M Hadjiiski, Heang-Ping Chan, Jun Wei, Mark A Helvie, "Computer Aided Detection of Clusters of Microcalcifications on Full Field Digital Mammograms," *Med Phys*, vol. 33, no. 8, pp. 2975–2988, (2006).

[10]. H. BilginKesercia, "Computerized detection of pulmonary nodules in chest radiographs based on morphological features and wavelet snake model," *Med Image Anal*, vol. 6, no. 4, pp. 431–447, (2002).

[11]. .Giuseppe Coppini, "Neural Networks for Computer-Aided Diagnosis: Detection of Lung Nodules in Chest Radiograms," *IEEE Trans Inf Technol Biomed*, vol. 7, no. 4, pp. 344–357, (2004).
[12]. E. I. Mohamed and C. Maiolo, "specific bone mineral density Artificial neural network analysis : a novel application for predicting site-specific bone mineral density," (2003).
[13]. MarcoGori, "Deep Architectures," in *Machine Learning A Constraint- Based Approach*, pp. 236–338, Elsevier Ltd, (2018)..
[14]. Z. C. Lipton, J. Berkowitz, and C. Elkan, "A Critical Review of Recurrent Neural Networks for Sequence Learning," (2015).
[15]. .M. S. Islam, F. A. Foysal, N. Neehal, E. Karim, and S. A. Hossain, "IncePTB: A CNN based classification approach for recognizing traditional Bengali games," *Procedia Comput Sci*, vol. 143, no. May, pp. 595–602 (2018).
[16]. A. Alexander SelvikvågLundervold, "An overview of deep learning in medical imaging focusing on MRI," *Z Med Phys*, vol. 29, no. 2, pp. 102–127.
[17]. K. O'Shea and R. Nash, "An Introduction to Convolutional Neural Networks," no. November, (2015).
[18]. C.-Z. X. Mingyi Zhu, Kejiang Ye, "Network Anomaly Detection and Identification Based on Deep Learning Methods," in *Cloud Computing*
– *CLOUD 2018*, Springer International Publishing, (2018).
[19]. D. WenluZhang, RongjianLi, HoutaoDeng, LiWang, WeiliLin, ShuiwangJi, "Deep convolutional neural networks for multi-modality isointense infant brain image segmentation," *Neuroimage*, vol. 108, pp. 214–224, (2015).
[20]. D. C. Cireşan, A. Giusti, L. M. Gambardella, and J. Schmidhuber, "Deep neural networks segment neuronal membranes in electron microscopy images," *Adv Neural Inf Process Syst*, vol. 4, pp. 2843– 2851 (2012).
[21]. A. Prasoon, K. Petersen, C. Igel, F. Lauze, E. Dam, and M. Nielsen, "Deep feature learning for knee cartilage segmentation using a triplanar convolutional neural network," *Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)*, vol. 8150 LNCS, no. PART 2, pp. 246–253, (2013).
[22]. H. G. Yaniv Bar, Idit Diamant, Lior Wolf, "Deep learning with non- medical training used for chest pathology identification," in *SPIE Medical Imaging*, (2015).
[23]. John Arevalo ; Fabio A. González ; Raúl Ramos-Pollán ; Jose L. Oliveira ; Miguel Angel Guevara Lopez, "Convolutional neural networks for mammography mass lesion classification," in *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, (2015).
[24]. T. Schlegl, J. Ofner, and G. Langs, "Unsupervised pre-training across image domains improves lung tissue classification," *Lect Notes Comput*
[25]. *Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics)*, vol. 8848, pp. 82–93, (2014).
[26]. H. Chen *et al.*, "Standard Plane Localization in Fetal Ultrasound via Domain Transferred Deep Neural Networks," *IEEE J Biomed Heal Informatics*, vol. 19, no. 5, pp. 1627–1636, (2015).
[27]. H. Salehinejad, S. Sankar, J. Barfett, E. Colak, and S. Valaee, "Recent Advances in Recurrent Neural Networks," no. March, (2017).
[28]. R. Pascanu, C. Gulcehre, K. Cho, and Y. Bengio, "How to construct deep recurrent neural networks," *2nd Int Conf Learn Represent ICLR 2014 - Conf Track Proc*, pp. 1–13, (2014).
[29]. 28.P. Meyer, V. Noblet, C. Mazzara, and A. Lallement, *Survey on deep learning for*

radiotherapy, vol. 98. Elsevier Ltd, (2018).

[30]. F. Liu, H. Jang, R. Kijowski, T. Bradshaw, and A. B. Mcmillan, "Deep learning Mr imaging-based attenuation correction for PeT/Mr imaging

[31]. 1 TECHNICAL DEVELOPMENTS: Deep Learning MR Imaging- based Attenuation Correction for PET/MR Imaging Liu et al," *Radiol n Radiol*, vol. 286, no. 2, (2018).

[32]. A. Mehranian, H. Arabi, and H. Zaidi, "Vision 20/20: Magnetic resonance imaging-guided attenuation correction in PET/MRI: Challenges, solutions, and opportunities," *Med Phys*, vol. 43, no. 3, pp. 1130–1155 (2016).

[33]. W. Han *et al.*, "Deep transfer learning and radiomics feature prediction of survival of patients with high-grade gliomas," *Am J Neuroradiol*, vol. 41, no. 1, pp. 40–48, (2020).

[34]. Luke Oakden-Rayner, "Precision Radiology: Predicting Longevity Using Feature Engineering and Deep Learning Methods in a Radiomics Framework," *Sci Rep*, vol. 7, no. 1 (2017).

[35]. V. Gulshan *et al.*, "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *JAMA - J Am Med Assoc*, vol. 316, no. 22, pp. 2402– 2410, (2016).

[36]. Mohammadhassan Izadyyazdanabadi, Evgenii Belykh,Michael A. Mooney, Jennifer M. Eschbacher, Peter Nakaji, Yezhou Yang, Mark C. Preul, "Prospects for Theranostics in Neurosurgical Imaging: Empowering Confocal Laser Endomicroscopy Diagnostics via Deep Learning," *Front Oncol*, vol. 8, (2018).

[37]. G. Litjens *et al.*, "State-of-the-Art Deep Learning in Cardiovascular Image Analysis," *JACC Cardiovasc Imaging*, vol. 12, no. 8P1, pp. 1549–1565, (2019).

[38]. B. C. Yang YJ, "Application of artificial intelligence in gastroenterology," *World J Gastroenterol*, vol. 25, no. 14, pp. 1666– 1683.

[39]. T. Renukadevi and S. Karunakaran, "Optimizing deep belief network parameters using grasshopper algorithm for liver disease classification," *Int J Imaging Syst Technol*, vol. 30, no. 1, pp. 168–184, (2020).

[40]. Lakshmanaprabu S.K, Mohanty.S. N,Sheeba Rani,, Sujatha Krishnamoorthy, Uthayakumar ,Sankar(2019"Online clinical decision support system using optimal deep neural networks" Volume 81, August 2019, 105487, Applied Soft Computing, Elsevier

[41]. K.Venkatachalam, N.K.Karthikeyan, S.Lavanya, 2016. A Framework for Constraint Based Web Service Discovery with Natural Language User Queries. International Conference on Engineering Technology and Science (ICETS'16)