Aashutosh Kharb et al. International Journal of Recent Research Aspects ISSN: 2349-7688, Vol. 10, Issue 1, March 2023, pp. 1-7

Brain Tumor Detection Using Deep Learning: A Study

Aashutosh Kharb[1], Prachi Chaudhary[2]

[1]Research Scholar, ECE Department, DCRUST Murthal
[2]Assistant Professor, ECE Department, DCRUST Murthal

Abstract
The mortality rate due to brain tumors is increasing every year. Therefore, it is very much needed to detect it at the earliest and start the diagnosis. The advancement in the techniques like machine and deep learning, artificial intelligence etc., the neuroscience get a helping hand for timely identification, classification and diagnosis of brain tumors. Herein, this review provides an analysis to brain tumor detection and diagnosis using deep learning. This study also provide the details of potential datasets that can be used for the detection and classification of brain tumors. Further, the potential deep learning models which are suitable for brain tumor classification is summarized. This study also identifies the problems that one can face during analysis of brain tumors and the suggested solution for the same.

Keywords: *Brain Tumor, Deep learning, Datasets, Imaging Modalities, MRI, Machine Learning*

I. INTRODUCTION

In order to detect, diagnose and early treatment of diseases numerous imaging methodologies like CT scan, PET, MRI, X-ray, ultrasound, mammography etc. have been used in medical field. Nowadays, researchers are using machine (ML) and deep (DL) learning techniques are for the precise interpretation, analysis of these images [9], [10].

The deep learning has the benefit over machine learning, as it incorporates feature engineering in its learning phase[11], [12]. This results in removal of manual extraction of features and require only minor data pre-processing. The other factors that contributes in the popularity of deep learning are as follows. Firstly, the use of graphics processing units (GPUs) and high-tech central processing units (CPUs). Secondly, the availability of big data. Thirdly, the availability of public datasets like ImageNet for testing and training the deep neural network and to design new model. Further, various optimization techniques are there which can be used to get an optimal solution.

Applications of deep learning for medical application domain include tissue segmentation, anatomical and cellular structure recognition, image registration and localization, feature learning, and computer-aided disease prognosis and diagnosis [13].

Medical imaging is one of the crucial and critical area of area of research both in the field of scientific research and medical research. The improvement of surgical planning and precision utilising human-machine intervention is a result of developments in medical imaging, such as computerised medical picture segmentation and computer-aided design. This combines the treatment strategy with the advancement of imaging technology to deliver some of the most useful diagnostic equipment in the medical industry [1], [2].

Among these, the MRI and CT scan are the two principal non-invasive methods utilised to investigate the human brain. The nuclear magnetic resonance (NMR) principles are the foundation of the MRI, a medical diagnostic tool used to examine the human anatomy and reveal details about the composition of materials.

Because it frequently requires a vast amount of data, brain tumor analysis is one of the most significant and challenging tasks in many medical picture applications. Patient mobility, a short capture period, and poorly defined soft tissue boundaries are all common causes of artefacts [3], [4]. Different kinds of tumors come in a wide range of sizes and shapes. Despite having distinct picture intensities, they may appear to be different sizes and types. Some of them might also influence the picture intensity around the tumor by influencing nearby structures [5], [6].

The radiologists focus on three specific regions of the brain while analyzing the MRI scans, that is, grey matter, white matter and cerebrospinal fluid as shown in Figure 1.

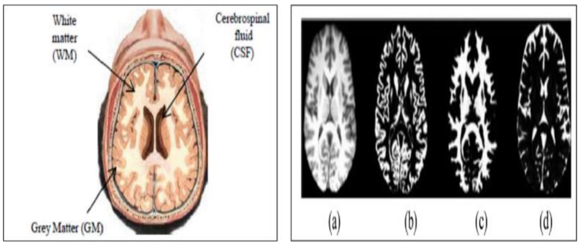

Figure 1: General Brain Image and MRI scans of (a) General Image (b) GM (c) WM (d) CSF[7]

Further, the MRI has been taken into three directions that is axial, saggital and coronal as shown in Figure 2.

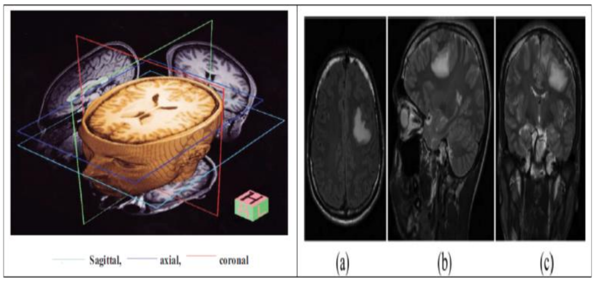

Figure 2: Directions of MRI imaging [2], [7]

Additionally, according to the World Health Organization (WHO), 120,000 people died last year and there are an estimated 400,000 brain tumor patients worldwide [8]. Medical professionals need to validate the regions and borders of the brain tumor, pinpoint its precise location, and identify the precise affected area before treating the patient with chemotherapy, radiotherapy, or brain surgery. The tool can be automatic or semi-automatic for brain tumor segmentation, which aids in reviewing the negative consequences of cancer and also serves as a prerequisite stage for doctors to detect the brain tumor before performing procedures.

The structure and physiology of the brain tumor are determined using MR-based imaging techniques. Finding the tumor's location, size, amount of necrosis, vascular supply, and accompanying edoema is of special importance to clinicians. A pertinent differential diagnosis can be produced using a variety of imaging modalities. Contrast agents, fat suppression, MR angiography, functional MRI, diffusion weighted imaging (DWI), MR spectroscopy, and fast fluid-attenuated inversion-recovery (FLAIR) are some of the current methods utilised to image brain tumors [2], [6].

This article provides a review related to brain tumor analysis using deep learning and try to provide the answer to the following questions:

a) What is the anatomy of brain tumor classification?
b) What are the potential datasets?
c) What are the major deep learning models that can be used for brain tumor detection and classification?
d) What are the major issues and their potential solutions that arise in deep learning based brain tumor detection?

The rest of this article has been organized as follows. Section 2 discusses the anatomy of brain tumor classification. Section 3 brief out the major datasets while section 4 provides the basic block diagram for brain tumor analysis using deep learning. Section 4 highlights the major issues associated with deep learning based brain tumor detection and classification, followed by conclusion and future work.

II. ANATOMY OF BRAIN TUMOR CLASSIFICATION

The following types of brain tumors are categorised by the World Health Organization (WHO): astrocytoma, low grade (grades I and II), high grade (grades III and IV), ganglioglioma, oligodendroglioma, ependymoma, and medulloblastoma [8]. The tumor becomes more malignant as the grade rises. The tumor grading aids in the understanding of the patient's condition by the physician, the patient, and family members. It also aids in treatment planning and outcome prediction for the physician.

The least malignant tumors are those with a grade of I, which is typically suggestive of long-term survival. When observed under a microscope, these tumors appear almost normal and have a sluggish rate of growth. The only effective treatment for this grade of tumor may be surgery. Examples of grade I tumors include pilocytic astrocytoma, craniopharyngioma, and other neuronal tumors including gangliocytoma and ganglioglioma. [2], [8]. Grade II tumors have a modest rate of growth and exhibit a little aberrant appearance. Some can recur as higher grade tumors and extend into the neighbouring normal tissue. Although there is not usually a significant difference between grade II and grade III tumors, grade III tumors are by definition malignant. A grade III tumor's cells aggressively divide to create aberrant cells that spread into neighbouring healthy brain tissue. These grade IV cancers frequently recur. Tumors in grade IV are the most dangerous. Under a microscope, they can appear strange, and they can encroach on neighbouring healthy brain tissue. These tumors create fresh blood vessels to support their continued rapid growth. In their centres, there are also pockets of dead cells. The most frequent type of grade IV tumor is the glioblastoma multiform.

Secondly, on the basis of location of the tumor, the tumor can be local, regional or distant. Third criteria is radiological appearance which specifies the size of the tumor whether it is enhancing or not and even if it is enhancing it has some side effects like edema or not. Finally, the brain tumors can also be classified whether there is large or small deformation in the brain.

These four classification criteria for brain tumors as shown in Figure 3.

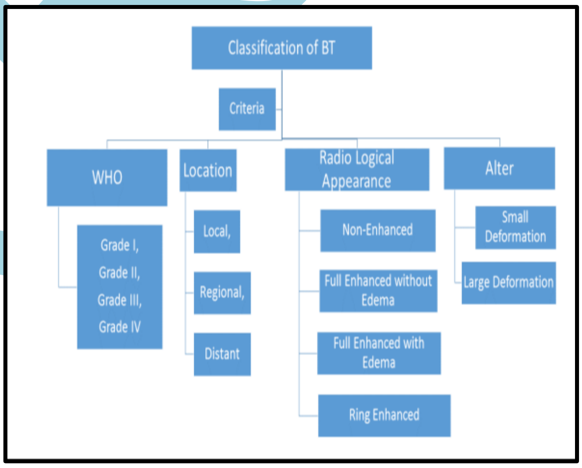

Figure 3:Classification of Brain Tumor

1. Brain Tumor Analysis using Deep Learning

The development of deep learning applications to brain analysis has been shown in Figure 4.

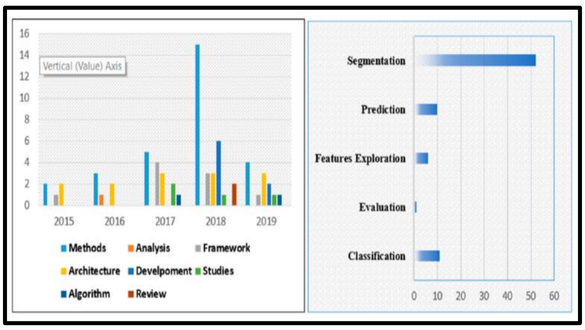

Figure 4:Distribution of No. of Articles for Brain Analysis [14]

It has been seen that the major work for brain analysis is done for segmentation which is to identify or extract tumor region for detection, prediction and classification and very less work has been done for classification. Therefore, in this work our focus is on brain tumor detection and classification. Figure 5 shows the basic block diagram for the brain MRI analysis. The overall procedure consists of four main stages, including pre-processing, data-preparation, segmentation, and post-processing [1], [15]–[18]. Different pre-processing tasks are required after acquiring MRI so that the images can be used for the segmentation of various tissue types of the brain. They are skull stripping, bias field correction,denoising and image registration.

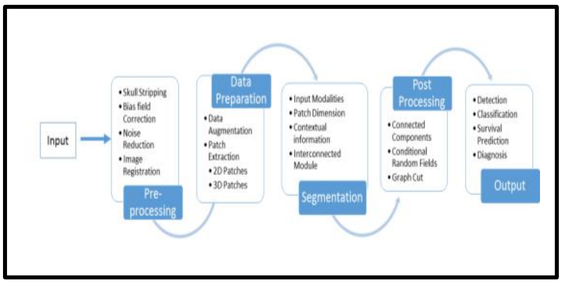

Figure 5:General Block Diagram for Brain MRI Analysis using Deep Learning

III. BRAIN TUMOR DETECTION AND CLASSIFICATION USING DEEP LEARNING

The various deep learning models are most widely used are convolutional neural network (CNN), recurrent neural network (RNN), long short term memory (LSTM), Generative Adversarial Network (GAN). [1], [10], [19]–[25] [26], [27], transfer learning and extreme learning. This section provides the literature review related to the use of various deep learning models for brain tumor detection and classification.

The very first deep learning(DL) based efforts were done using FCN that is fully convolutional network to perform semantic segmentation [28]. An FCN can take any size image and results into same sized segmentation map because it only has convolutional layers. In order to handle non-fixed sized input and output, the authors changed current DL architectures, by swapping fully-connected-layers with FCN. Hence, in place of classification score, a feature map known as segmentation map is generated as output. This research is regarded as a turning point in the field of image segmentation since it shows how deep networks may be end-to-end trained for semantic segmentation on a range of image sizes. The FCN are widely used for segmentation of brain tumor [29], skin lesions [31], and iris detection [32], instance aware semantic segmentation [30].

The U-net is proposed in [33] where network and training technique uses data augmentation to make better use of the given annotated images. A symmetric expanding path that allows for exact localisation and a contracting path that captures context make up the U-Net design. For various types of data, many U-Net extensions have been created, for 3D images [34], nested U-Net [35], for road segmentation [36].

In [37] the architecture of V-net has been specified for 3D medical images where the major issue is of class imbalance arises due to the voxel quantity in foreground and background. The further applications of V-net are described in [38] for lesions.

The faster R-CNN model has been designed for object detection[39]. The bounding boxes has been computed in RPN layer by defining the regions. After that, the Region of Interest (RoI) has been extracted, and the features has been extracted by RoIPool layer. These features are further used to classify the objects into various classes.

The various variants of RCNN has been proposed to improve its performance like Mask R-CNN [40], PANet [41] , MaskLab [42], R-FCN [43], DeepMask [44], SharpMask [45], PolarMask [46], [47].

In [48] ReSeg has been proposed to enhance the performance of ReNet [49]. In [50] LSTM based model has been designed for classification of scene images using pixel level information.

The authors in [51] proposed the multi-scale Pyramid Scene Parsing Network (PSPN), a scene's overall context can be learned more effectively. Here, they have used ResNet with a dilated network as feature extractor. Laplacian pyramid based multi-resolution reconstruction architecture has been proposed in [52]. Some other multi-scale models are DM-Net [53], CCN [54], APC-Net [55], MSCI [56] and salient object segmentation [57]

In [58] , the authors have proposed a classification system using deep transfer learning and retrained Google net to extract features from brain MRI images. They had applied 5-fold cross validation process on the data set from figshare. They have classified the brain tumor into three classes and showed that their classification system has accuracy of 98% .

The authors in [59] combines deep wavelet autoencoders with deep neural networks and used it for classification and segmentation task. they have compared it with existing model and shows that the proposed model gives an overall accuracy of 96%.

In [60] the author had proposed a computer aided detection system for classifying the brain tumor using deep learning and wavelet transform. The system shows an overall accuracy of 99% on the data from figshare.

The authors in [61] have proposed a CNN based architecture for brain tumor classification into 3 broad categories that is meningiomas, gliomas and pituitary tumor. The authors gets the best result for the proposed model with 10 fold cross validation and gets an accuracy of 96.56%. They have used T1- weighted contrast enhanced MRI image dataset.

In [62] the authors have also proposed DL based models to classify different brain tumor types. The model proposed provides two types of classification firstly into meningiomas, gliomas and pituitary tumor. Secondly into grade II, grade III and grade IV. They are also used 2 drop out layers to prevent overfitting there.

Table 1: Summary of Brain Tumor Classification using Deep Learning

S.No	Author and Year	DL Model	Dataset	Additional Method	Accuracy	No. of Classes
1)	S.Deepak[58], 2019	CNN (GoogLeNet)	figshare	Transfer learning	92.3%	3
2)	P.S.Mallick *et.al.*[59], *2018*	Autoencoder	RIDER	Wavelet Transform	93%	-
3)	A.M.Sarhan [60], 2020	CNN	figshare	DWT	99.3%	3
4)	M.M.Badza [61], 2020	CNN	Hospitals	-	97.2%	3
5)	H.H.Sultan [62], 2019	CNN	REMBRANDT	-	96.13%	3
6)	M.Sajjad [63], 2018	CNN	radiopedia	Data Augmentation	90.67%	3

The major characteristic of these algorithms are summarized in Table 1.

After studying the literature, the basic functionality related to brain analysis using deep learning or machine learning has been summarized in Figure 6. In order to perform brain analysis, the input is taken in the form of images. The source of input images can be the hospitals or from the diagnostic centers. Further, the images can be either from single imaging modality or with multiple imaging modalities like PET, CT scan, and MRI etc. These images are then checked for any abnormality in brain. Therefore, if there is no issues in the brain then there is no need to investigate further. However, if there are some issues then it may be a tumor or some other abnormality like stroke, lesion etc. Hence, after detecting that there is some abnormality is present in the brain and hence the next is to identify and classify the abnormality, such as in case of tumor whether it is benign or malignant, in which grade and category it belongs to.

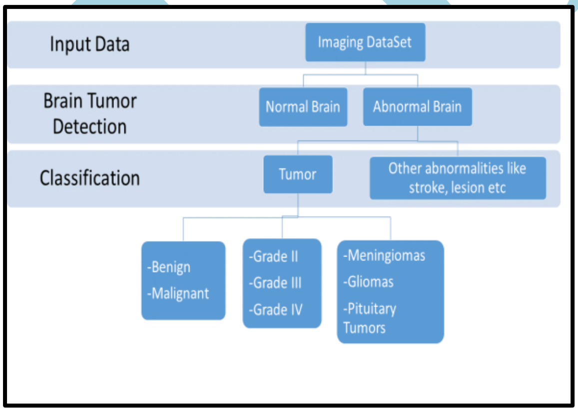

Figure 6:Taxonomy of Brain Analysis

IV. RESEARCH GAPS AND MOTIVATION

After studying the literature, potential research gaps for brain tumor detection using deep learning have been identified which can be broadly classify into two categories, viz , research gaps associated with datasets and the issues associated with deep models. These are summarized in Figure 7.

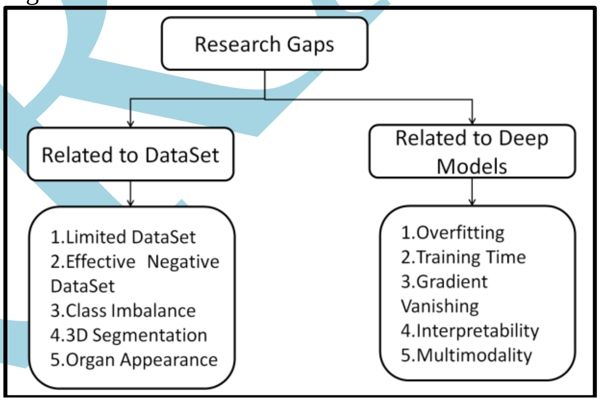

Figure 7 : Research Gaps

Related to Dataset

Limited Dataset.

Deep learning will greatly improve the performance of classification algorithm when the number of training samples is very large. This task of collecting huge datasets of medical images is very tough and challenging task and performing annotations on it is further very expensive and tedious. Data augmentation, transfer learning, generative adversial network (GAN), batch-wise training etc are the different ways to increase the data size.

Effective Negative Set.

In order to enhance and visualize the effect of the model, the dataset must contain which are negative in nature and it is very difficult to gather false positive data. Thus, collection of negative sample set is the another challenge.

Class Imbalance.

In case of medical imaging, even if a large amount of data is available but area of interest is very less. In other words, the organ or tumor which is of greater interest is very less (or small).

3D Segmentation.

Nowadays, 3D image segmentation is gaining popularity, so there is a strong need for large-scale dataset with 3D images. The 3D data is more voluminous than 2D data and is more challenging to deal with as there is low-variance exist between the target and neighboring pixels.

Organ Appearance.

One of the main obstacles to brain tumor analysis is the target tumor's heterogeneous appearance. From patient to patient, the tumor or lesion may differ greatly in terms of its size, shape, and location. An inherent imaging obstacle is the hazy boundary with low contrast between the targeted organs and the surrounding tissues. Attenuation coefficient in CT and relaxation time in MRI are typically to blame for this. Approaches based on many modalities can solve this issue. Additionally, segmenting overlapping or bordering organs is known to be aided by the information provided by superpixels.

V. RELATED TO DEEP LEARNING MODELS OVERFTTING.

The dataset's bais-variance tradeoff results in the overfitting issue. Overfitting typically occurs when a model can reasonably better capture the patterns and regularities in the training set. The short size of the training dataset is the primary cause of overfitting. By using dropout and dropout connects, as well as increasing the quantity of the data, this issue can be solved.

Training Time.

Reducing the training time and having faster convergence is a core topic of many studies. Some of the methods to reduce the training time is to use pooling layers, convolution with stride and batch-normalization.

Gradient Vanishing.

The final loss cannot be successfully back propagated to shallow layers. This issue is more acute with the 3D models. Gradient vanishing is typically solved using deeply supervised approaches, in which the output of the intermediate hidden layers is scaled up via deconvolution and supplied to a softmax to achieve the prediction.

Interpretability.

What precisely are deep learning models? How are we to interpret the qualities that these models have learned? What is a basic neural architecture capable of a specific level of dataset segmentation accuracy? Although there are various methods for visualising the learnt convolutional kernels of these models, there hasn't been a thorough examination of their fundamental dynamics or behaviour. The creation of better models tailored to different segmentation scenarios may be made possible by a greater knowledge of these models' theoretical underpinnings.

Multimodality.

The multimodality can provide multi-information about a tumor, organ or body part. The multi-modal images help to extract features from different views and help to provide better data representation and increase the strength of networks.

VI. REFERENCES

[1] A. S. Lundervold and A. Lundervold, “An overview of deep learning in medical imaging focusing on MRI,” *Zeitschrift fur Medizinische Physik*, vol. 29, no. 2, pp. 102–127, 2019.

[2] K. A. Rajasekaran and C. C. Gounder, “Advanced Brain Tumor Segmentation from MRI Images,” *High-Resolution Neuroimaging - Basic Physical Principles and Clinical Applications*, 2018.

[3] M. A. Khan *et al.*, “Brain tumor detection and classification: A framework of marker-based watershed algorithm and multilevel priority features selection,” *Microscopy Research and Technique*, vol. 82, no. 6, pp. 909–922, 2019.

[4] A. M. Rauschecker *et al.*, “Artificial intelligence system approaching neuroradiologist-level differential diagnosis accuracy at brain MRI,” *Radiology*, vol. 295, no. 3, pp. 626–637, 2020.

[5] “Types of Brain Tumors.” [Online]. Available: https://www.aans.org/en/Patients/Neurosurgical-Conditions-and-Treatments. [Accessed: 10-Jul-2020].

[6] “Classification of Brain Tumors.” [Online]. Available: https://www.aans.org/en/Media/Classifications-of-Brain-Tumors. [Accessed: 10-Jul-2020].

[7] A. Tiwari, S. Srivastava, and M. Pant, “Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019,” *Pattern Recognition Letters*, vol. 131, pp. 244–260, 2020.

[8] D. N. Louis *et al.*, “The 2016 World Health Organization Classification of Tumors of the Central Nervous System: a summary,” *Acta Neuropathologica*, vol. 131, no. 6, pp. 803–820, 2016.

[9] T. Zhou, S. Ruan, and S. Canu, “A review: Deep learning for medical image segmentation using multi-modality fusion,” *Array*, vol. 3–4, no. May, p. 100004, 2019.

[10] S. Minaee, Y. Boykov, F. Porikli, A. Plaza, N. Kehtarnavaz, and D. Terzopoulos, “Image Segmentation Using Deep Learning: A Survey,” pp. 1–23, 2020.

[11] Onyema, E. M., Lilhore, U. K., Saurabh, P., Dalal, S., Nwaeze, A. S., Chijindu, A. T., ... & Simaiya, S. (2023). Evaluation of IoT-Enabled hybrid model for genome sequence analysis of patients in healthcare 4.0. Measurement: Sensors, 26, 100679..

[12] D. Shen, G. Wu, and H. Suk, “Deep Learning in Medical Image Analysis,” *Annu. Rev. Biomed. Eng.*, vol. 19, pp. 221–250, 2017.

[14] M. W. Nadeem *et al.*, “Brain tumor analysis empowered with deep learning: A review, taxonomy, and future challenges,” *Brain Sciences*, vol. 10, no. 2, pp. 1–33, 2020.

[15] K. R. Laukamp *et al.*, “Fully automated detection and segmentation of meningiomas using deep learning on routine multiparametric MRI,” *European Radiology*, vol. 29, no. 1, pp. 124–132, 2019.

[16] A. A. S. Lundervold *et al.*, “Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images,” *Computers in*

Biology and Medicine, vol. 10, no. 1, pp. 9249–9261, 2020.

[17] S. Tchoketch Kebir, S. Mekaoui, and M. Bouhedda, “A fully automatic methodology for MRI brain tumor detection and segmentation,” *Imaging Science Journal*, vol. 67, no. 1, pp. 42–62, 2019.

[18] S. Sajid, S. Hussain, and A. Sarwar, “Brain Tumor Detection and Segmentation in MR Images Using Deep Learning,” *Arabian Journal for Science and Engineering*, vol. 44, no. 11, pp. 9249–9261, 2019.

[19] H. P. Chan, R. K. Samala, L. M. Hadjiiski, and C. Zhou, “Deep Learning in Medical Image Analysis,” *Advances in Experimental Medicine and Biology*, vol. 1213, pp. 3–21, 2020.

[20] M. H. Hesamian, W. Jia, X. He, and P. Kennedy, “Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges,” *Journal of Digital Imaging*, vol. 32, no. 4, pp. 582–596, 2019.

[21] A. Smailagic *et al.*, “O-MedAL: Online active deep learning for medical image analysis,” *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 10, no. 4, pp. 1–15, 2020.

[22] S. Asgari Taghanaki, K. Abhishek, J. P. Cohen, J. Cohen-Adad, and G. Hamarneh, *Deep semantic segmentation of natural and medical images: a review*, no. 0123456789. Springer Netherlands, 2020.

[23] X. Xie, J. Niu, X. Liu, Z. Chen, and S. Tang, “A Survey on Domain Knowledge Powered Deep Learning for Medical Image Analysis,” pp. 1–26, 2020.

[24] F. Lateef and Y. Ruichek, “Survey on semantic segmentation using deep learning techniques,” *Neurocomputing*, vol. 338, pp. 321–348, 2019.

[25] F. Sultana, A. Sufian, and P. Dutta, “Evolution of Image Segmentation using Deep Convolutional Neural Network: A Survey,” *Knowledge-Based Systems*, vol. 201–202, pp. 1–48, 2020.

[26] K. Fukushima, “Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position,” *Biological cybernetics*, vol. 36, no. 4, pp. 193–202, 1980.

[27] S. Egmentation, D. L. Pham, C. Xu, and J. L. Prince, “Current methods in medical image segmentation,” *Annual review of biomdeical Enginnering*, pp. 315–337, 2000.

[28] and T. D. J. Long, E. Shelhamer, “Fully convolutional network for semantic segmentation,” in *IEEE conference on computer vision and pattern recognition*, 2015, pp. 3431–3440.

[29] T. V. G. Wang, W. Li, S. Ourselin, “Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks,” *International MICCAI Brainlesion Workshop. Springer*, pp. 178–190, 2017.

[30] Y. W. Y. Li, H. Qi, J. Dai, X. Ji, “Fully convolutional instanceaware semantic segmentation,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017, pp. 2359–2367.

[31] Y.-C. Lo Y. Yuan, M. Chao, “Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance,” *IEEE transactions on medical imaging*, vol. 36, no. 9, pp. 1876–1886, 2017.

[32] and T. T. N. Liu, H. Li, M. Zhang, J. Liu, Z. Sun, “Accurate iris segmentation in non-cooperative environments using fully convolutional networks,” in *2016 International Conference on Biometrics (ICB). IEEE*, 2016, pp. 1–8.

[33] T. B. O. Ronneberger, P. Fischer, “U-net: Convolutional networks for biomedical image segmentation,” in *International Conference on Medical image computing and computer-assisted intervention. Springer*, 2015, pp. 234–241.

[34] and O. R. O¨ . C¸ ic¸ek, A. Abdulkadir, S. S. Lienkamp, T. Brox, “3d u-net: learning dense volumetric segmentation from sparse annotation,” in *International conference on medical image computing and computer-assisted intervention. Springer*, 2016, pp. 424–432.

[35] and J. L. Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, “Unet++: A nested u-net architecture for medical image segmentation,” in *Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support,Springer*, 2018, pp. 3–11.

[36] and Y. W. Z. Zhang, Q. Liu, “Road extraction by deep residual u-net,” *IEEE Geoscience and Remote Sensing Letters*, vol. 15, no. 5, pp. 749–753, 2018.

[37] and S.-A. A. F. Milletari, N. Navab, “V-net: Fully convolutional neural networks for volumetric medical image segmentation,” in *2016 Fourth International Conference on 3D Vision (3DV). IEEE*, 2016, pp. 565–571.

[38] and R. T. T. Brosch, L. Y. Tang, Y. Yoo, D. K. Li, A. Traboulsee, “Deep 3d convolutional encoder networks with shortcuts for multiscale feature integration applied to multiple sclerosis lesion segmentation,” *IEEE transactions on medical imaging*, vol. 35, no. 5, pp. 1229–1239, 2016.

[39] and J. S. S. Ren, K. He, R. Girshick, “Faster r-cnn: Towards realtime object detection with region proposal networks,” in *Advances in neural information processing systems*, 2015, pp. 91–99.

[40] Dalal, Surjeet, Pallavi Goel, Edeh Michael Onyema, Adnan Alharbi, Amena Mahmoud, Majed A. Algarni, and Halifa Awal. "Application of Machine Learning for Cardiovascular Disease Risk Prediction." Computational Intelligence and Neuroscience 2023 (2023)..

[41] J. J. S. Liu, L. Qi, H. Qin, J. Shi, “Path aggregation network for instance segmentation,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 8759–8768.

[42] A. L.-C. Chen, A. Hermans, G. Papandreou, F. Schroff, P. Wang and H. Adam, “Masklab: Instance segmentation by refining object detection with

semantic and direction features," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 4013–4022.

[43] Edeh, Michael Onyema, Surjeet Dalal, Ibidun Christiana Obagbuwa, BVV Siva Prasad, Shalini Zanzote Ninoria, Mohd Anas Wajid, and Ademola Olusola Adesina. "Bootstrapping random forest and CHAID for prediction of white spot disease among shrimp farmers." Scientific Reports 12, no. 1 (2022): 20876..

[44] P. D. P. O. Pinheiro, R. Collobert, "Learning to segment object candidates," in *Advances in Neural Information Processing Systems*, 2015, pp. 1990–1998.

[45] P. D. P. O. Pinheiro, T.-Y. Lin, R. Collobert, "Learning to refine object segments," in *European Conference on Computer Vision. Springer*, 2016, pp. 75–91.

[46] A. E. Xie, P. Sun, X. Song, W. Wang, X. Liu, D. Liang, C. Shen and P. Luo, "Polarmask: Single shot instance segmentation with polar representation," *arXiv preprint*, 2019.

[47] M. S. Z. Hayder, X. He, "Boundary-aware instance segmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017, pp. 5696–5704.

[48] Y. B. F. Visin, M. Ciccone, A. Romero, K. Kastner, K. Cho and and A. C. M. Matteucci, "Reseg: A recurrent neural network-based model for semantic segmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 2016, pp. 41–48.

[49] A. F. Visin, K. Kastner, K. Cho, M. Matteucci, A. Courville and Y. Bengio, "Renet: A recurrent neural network based alternative to convolutional networks," *arXiv preprint*, 2015.

[50] M. L. W. Byeon, T. M. Breuel, F. Raue, ""Scene labeling with lstm recurrent neural networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 3547–3555.

[51] Dalal, Surjeet, Edeh Michael Onyema, Pawan Kumar, Didiugwu Chizoba Maryann, Akindutire Opeyemi Roselyn, and Mercy Ifeyinwa Obichili. "A hybrid machine learning model for timely prediction of breast cancer." International Journal of Modeling, Simulation, and Scientific Computing (2022): 2341023..

[52] G. G. and C. C. Fowlkes, "Laplacian pyramid reconstruction and refinement for semantic segmentation," in *European Conference on Computer Vision. Springer*, 2016, pp. 519–534.

[53] and Y. Q. J. He, Z. Deng, "Dynamic multi-scale filters for semantic segmentation," in *Proceedings of the IEEE International Conference on Computer Vision*, 2019, pp. 3562–3572.

[54] and G. W. H. Ding, X. Jiang, B. Shuai, A. Qun Liu, "Context contrasted feature and gated multi-scale aggregation for scene segmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 2393–2402.

[55] and Y. Q. J. He, Z. Deng, L. Zhou, Y. Wang, "Adaptive pyramid context network for semantic segmentation," in *Conference on Computer Vision and Pattern Recognition*, 2019, pp. 7519–7528.

[56] Dalal, Surjeet, Edeh Michael Onyema, and Amit Malik. "Hybrid XGBoost model with hyperparameter tuning for prediction of liver disease with better accuracy." World Journal of Gastroenterology 28, no. 46 (2022): 6551-6563.

[57] Onyema, Edeh Michael, Umesh Kumar Lilhore, Praneet Saurabh, Surjeet Dalal, Arinze Steve Nwaeze, Asogwa Tochukwu Chijindu, Lauritta Chinazaekpere Ndufeiya-Kumasi, and Sarita Simaiya. "Evaluation of IoT-Enabled hybrid model for genome sequence analysis of patients in healthcare 4.0." Measurement: Sensors 26 (2023): 100679..

[58] S. Deepak and P. M. Ameer, "Brain tumor classification using deep CNN features via transfer learning," *Computers in Biology and Medicine*, vol. 111, no. March, p. 103345, 2019.

[59] P. Kumar Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen, and P. Tiwari, "Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep Neural Network," *IEEE Access*, vol. 7, no. c, pp. 46278–46287, 2019.

[60] A. M. Sarhan, "Brain Tumor Classification in Magnetic Resonance Images Using Deep Learning and Wavelet Transform," *Journal of Biomedical Science and Engineering*, vol. 13, no. 06, pp. 102–112, 2020.

[61] M. M. Badža and M. C. Barjaktarović, "Classification of brain tumors from mri images using a convolutional neural network," *Applied Sciences (Switzerland)*, vol. 10, no. 6, 2020.

[62] S. H.H, S. N.M, and Atabany W.L, "Multi-Classification of Brain Tumor Images using Deep Neural Network," *IEEE Access*, vol. 7, no. 6, pp. 69215–69225, 2019.

[63] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, and S. W. Baik, "Multi-grade brain tumor classification using deep CNN with extensive data augmentation," *Journal of Computational Science*, vol. 30, pp. 174–182, 2019.

