An Efficient Deep Learning Algorithm for MRI Segmentation Using Kernel based CNN with M-SVM

Dr. Ayesha Banu [1], Associate Professor &Head, Dept.of CSE(DS), Vaagdevi College of Engineering, Warangal, India.
Santhosh Ramchander. N [2], Associate Professor, Dept. of CSE , Sreyas Institute of Engineering and Technology, Hyderabad, India.
and Ramya Laxmi. K [3] , Assistant Professor, Dept. of CSE , Sreyas Institute of Engineering and Technology, Hyderabad, India.

Abstract.
Image segmentation has contributed majorly on long-standing medical image processing. It used earlier considered as a minor study field in computer vision. But today the rapid evolution of deep learning and image processing in medical field using CNN model has become a major focus of study. This paper examines deep learning-based image segmentation. Initially the ideas and features of deep learning-based medical image processing are introduced. The prospective development route is widened by analyzing the three basic approaches of medical image segmentation including their precincts. A list of troublesome tissues or organs and their conventional segmentation procedures are also discussed. However, research on deep learning-based picture segmentation is still in its infancy. Medical photographs are scarce, and the data set contains only a few of these images. The generated photos are not clinically correct. These challenges are addressed by deep learning-based brain tumour segmentation. Using a database of brain tumours, this study used a kernel-based CNN with M-SVM to increase quality and minimise error rates. It is obvious that the proposed work is superior to previous work.

Keywords: M-SVM, CNN, LoG, CLAHE, Feature Extraction, SGLDM

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1. Introduction

Image segmentation is considered as the complicated operation in image processing. This is a hotspot in pattern recognition. This is a hindrance to 3D modelling and other cutting-edge technology. Segmentation divides a huge image into manageable parts. To be readily visible, a picture's target must be separated from its background. Background subtraction methods are currently being improved. [1] By combining new ideas and technology, we've discovered a general segmentation method that works on every image. With the advancement of hospital care, new medical enterprises are becoming increasingly popular. Clinicians most typically use CT, MRI, PET, X-ray, and ultrasound imaging, followed by CT and MRI (UI). Images of microscopy, peritoneum, and other usual RGB images are given.

To make a clinical diagnosis, doctors use CT and other mri scans [2]. So computer vision researchers focused on medical image processing. The rapid progression in the area of artificial intelligence and deep learning (DL) applied on picture segmentation has shown good performance in image categorization [3]. Deep learning outperforms traditional AI and computer imaging approaches in separation precision and reliability. Using artificial intelligence to divide medical data can assist doctors assess the extent of malignant tumours, quantify therapy effects, and reduce doctor workload. To adequately describe the various strategies, we used Google and ArXiv to obtain the most recent research on computer-aided diagnosis and learning.

Medical image processing conferences, like other premier events, are important information sources (Information Processing in Medical Imaging). We looked for papers that incorporated deep learning techniques. We promise to verify all findings. To assess the merits and downsides of current developments in medical image segmentation, this study looks at machine learning rather than past evaluations [4–6]. This research reviews the current state of the art in deep learning medical image segmentation and outlines potential stumbling blocks. This paper assesses modern medical imaging DL methodology, focusing on new releases as well as older methods. For three years, deep learning has been employed in medical picture analysis. A closer look at its network concept and approaches is required. Meanwhile, its pros and cons are debated. A list of current segmentation methods by organ and tissue type is also provided. A wide range of measures and benchmark datasets were provided to help users examine and train the system.

2. Problem Statement:

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Examining 2D or 3D images using computer image processing, medical image segmentation for segmentation, collection, muti reconstruction [7] and for display of human body parts, sick bodies and soft tissues. The closeness or differences between regions is used to partition the image into numerous regions. Diagnostic accuracy and precision can be considerably improved by using this method to do qualitative approach research on lesions and other areas of concern. Currently, the most common types of cells, tissues, and organs are used as the object. A set theory model can be used to explain medical image segmentation in general: Using a set of matching constraints I = 1, 2,...) and a picture of medicine, I, the goal of segmenting I is to get a split of it, notably:

$$\bigcup_{x=1}^{N} R_x = \mathbf{I}, \quad R_x \cap R_y = \varnothing, \quad \forall x \neq y,\ x, y \in [1, N] \tag{1}$$

(I = 1,2,...) is a communication similarity constraint that applies to all pixels in the picture area Rx. A similar distinction is made for Ry by using the coordinates x, y. This refers to the number of sub regions following division, which must be a positive number greater than or equal to 2. Segmenting medical images can be broken down into the following phases:

1. Training and validation sets of medical imaging data as well as the test sets are commonly obtained. Computer vision for image processing generally divides a data set into three components. The training dataset is used to model the system , the validation dataset is used to modify the parameters of the hyper model , and the testing dataset is used to evaluate the model's efficiency.
2. Conduct random rotations and randomized scaling on the supplied image to enhance the data set's size. To divide the medical picture, select the suitable medical segmentation technique and then export the selected features. Evaluation of the accuracy of the estimation. Effective performance metrics must be established to evaluate the efficacy of medical picture segment. As such, it's an essential step in the procedure.

3. Image Segmentation:

Image segmentation is the major research interest today in computer vision . Image segmentation divides an image into pieces based on attributes including grayscale, colour, spatial texture, and geometric patterns. As a result, these features appear to be similar in some places but distinct in others. Semantic, instance, and panoramic segmentation are all subcategories of image segmentation based on edge detection fine and coarse resolution. CT segmentation is a popular practise. Notable image segmentation-related studies include segmentation of satellite images , medical images and autonomous driving [8,9]. An MRI's size, position, appearance, and structure make segmentation problematic. Figure 1-2 shows the many issues that an MRI image of a brain cancer experiences when analysed.

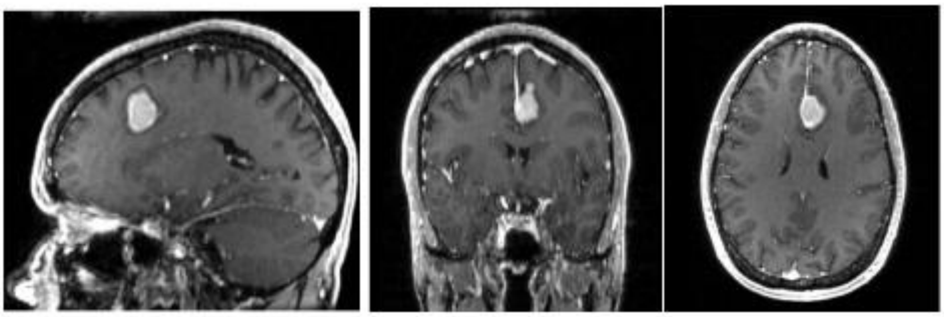

Figure 1: An MRI imaging of a brain tumour In various dimensions,

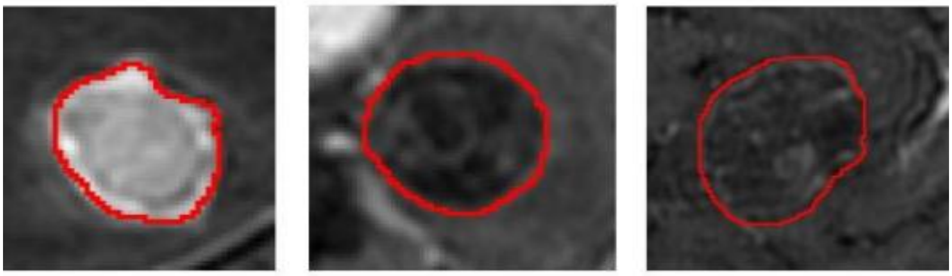

Figure 2: Various Visualizations of a Tumor in the Brain on MRI

The image segmentation algorithm improves step by step as the suggested network structure grows larger, resulting in more accurate results. However, there isn't a single segmentation technique that works for all types of photos. There is little comparison between traditional picture segmentation techniques and deep learning-based segmentation techniques now in use, but the fundamentals are still worth understanding about. Thresholds, regions, and edges are all examples of segmentation methods that have been presented [13, 14, 15, 16].

To divide the image, these approaches make use of digital image and mathematics. If you're looking for a fast and straightforward way to break up large datasets, this is the method for you. Image classification systems deep - learning - based have made significant progress over the past few decades. For the first time, their segmentation accuracy is superior than that of traditional methods. Image semantic categorization was successfully implemented for the first time using deep learning in a convolutionary neural network. This was the first picture segmentation algorithm to use convolution neural network. Full convolutional networks were presented by the researchers. It's also worth noting that several of the best segmentation networks including U-Net, Mask R-CNN, DeconvNet and RefineNet [16–18], excel at processing fine edges.

4. Research Objectives:

Organs and tissues make up the human body. There are differences between the various components. While the separation region for brain tumours and lung nodules is fairly large, the segmentation for blood vessels is required for retinal blood pictures. The latter necessitates greater precision in segmentation. Segmentation methods for different organs can be improved by extracting ideas from these messages. The aim of the research is to identify tumours at an early stage using a deep learning algorithm that accurately segmented the tumours. MRI image segmentation using a new deep learning model (based on a kernel-based CNN) and M-SVM.

An MRI picture is smoothed using the Laplacian of Gaussian filtering technique (LoG).
It is possible to use the Contrast Rough Approximation Histrogram Equalization (CLAHE) to improve an MRI picture and retrieve tumour form, shape, and surface details from the image.
Use the M-SVM algorithm for picture categorization based on characteristics you select.
Segmenting the tumour from an MRI picture is accomplished using the kernel-based CNN approach.

5. Methodology:

NNs that use convolutional neural networks Deep learning and image processing combine to produce the traditional CNN [19] model. A typical deep learning neural network, it has made substantial advances in image processing and analysis. There are various academic achievements that can be attributed to convolutional artificial neural networks (ann). supervised deep models, convolutional neural networks (CNNs) By reducing the number of parameters, geographical comparisons can be used to improve training outcomes. The convolutional neural network has undergone theoretical advancement, experimental progress, large-scale appliance, and in-depth investigation since its birth. An early stage of theory formation necessitates the use of this notion.

Hubel et al. [20] revealed in 1962 that multilayer receptive field excitation is employed to convey visual information from the retina to the brain. As far as we know, this is the very first concept for a receptive field. Using receptive fields, Fukushima [21] proposed a neurocognitive device in 1980. To put it another way, this is the first convolutional neural network. Using a gradient-based backpropagation technique, Lécun et al. [22] developed LeNet5, a supervised learning network. The LeNet5 handwriting recognition application sparked the academic community's interest in convolutional neural networks. After the LeNet5 network, an experimental cnns network was created. AlexNet's introduction in 2012 ushered in the era of convolutional neural networks in data-intensive applications. In machine learning, convolutional neural networks have emerged as a key research topic, and this examination will continue to expand.

2D CNN

A CNN has an input layer, an output layer, and several hidden layers. Convolution, pooling, and activation are all hidden layer operations. The number of neurons in each layer correlates to the input image's pixel count. This is done via convolution in the middle convolutional layer. The convolution results always depend on the kernel's parameters. A pooling layer, which filters and selects feature mappings, precedes the convolutional layer. The fully linked layers connect all neuron in the preceding level. To get a classifier's performance, we feed it back the output value. 2D CNNs are the most frequent type. This is done using a 2D convolution kernel like ResNet [24] or VGG -Visual Geometry Group [25]. Assume the input picture is H W and has RGB colour space. The convolution kernel slides on the image's spatial dimension. To obtain a value, the picture and (h, w) values are entered on each channel.

3D CNN

CT and MRI scans provide three-dimensional pictures. A 2D CT scan is only a slice of the complete picture. A 3D convolution kernel is required to segment diseased tissues. 3D U-Net, for example, uses a 3D convolution kernel. The U-Net network's 3D convolution kernel can now segment 3D medical images instead of the network's prior 2D one. A 3D CNN can represent volume better on all three axes X, Y, and Z. 3D segmentation completely exploits the benefits of spatial information. To compute the convolution kernel's height and width, we need the 3D image's channel and slice layer counts (C N H W). For 2D convolution, the window height, breadth, and layer count for each channel are adjusted.

Deep Learning Medical Image Segmentation Convolutional networks are effective at extracting and expressing features from images. It does not necessitate manual picture extraction or significant preparation. So CNN has been used in medical image segmentation for auxiliary diagnosis. The three important types of deep-learning methods for medical picture segmentation include: FCN, U-Net, and GAN. This paper shows the overview of each category along with the pros and cons of each strategy.

Fully Convolution Neural Networks

FCN is the most effective deep learning semantic segmentation method. This section evaluates FCN networks. Several FCN kinds are used. Categorization CNN networks like VGG and ResNet use FCN layers. The soft ax layer can recover chance data for each category, however it is one-dimensional. Only the entire image can be classified. This method is useless for image segmentation. This is why Long et al. [27] developed the convolution neural network. Five convolution layers of a CNN. Layers 6 and 7 are 4096 long and linked. The length of the eighth layer, a 1000-layer connected layer, represents 100,000 categories. FCN turns the three layers from 5 to 7 into convolution kernels of 7x7, 1x1, and 1x1. Then a softmax layer classifies each pixel. No need for segmentation. This network can handle any image size. The deconvolution layer rescaled the final convolution layer's feature subset. The source images' pixels can thus be predicted while keeping their spatial information. The convolution layer of the input image is then categorised pixel by pixel. These are FCN-32, FCN-16, and FCN-8.

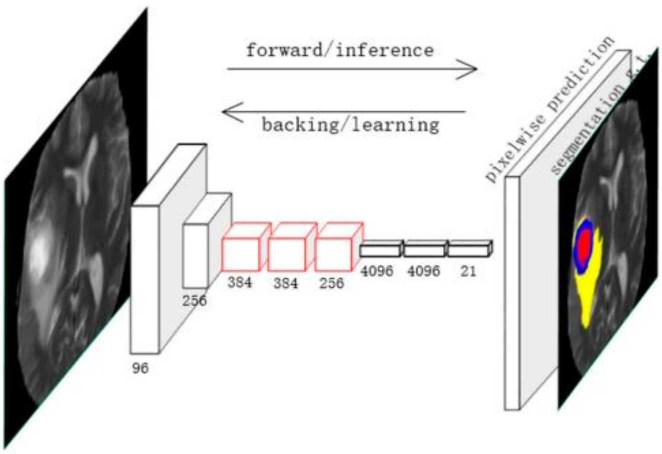

Figure 3: (FCN) Structure

Table 1: Brain MRI segmentation using CNN algorithms

Reference	Object	Modalities	Network Type	Data Set
Myronenko et al. [28]	Brain	MRI	FCN	BRATS2018
Nie et al. [29]	Brain	MRI	3D FCN	Infant brain images
Wang et al. [30]	Brain	MRI	FCN	ANDI data set and NITRC data set
Borne et al. [31]	Brain	MRI	3D U-Net	62 healthy brain images
Casamitjana et al. [32]	Brain	MRI	V-Net	BRATS2017
Moeskops et al. [33]	Brain	MRI	GAN	MRBrainS13
Rezaei et al. [34]	Brain	MRI	cGAN	BRATS 2017
Giacomello et al. [35]	Brain	MRI	SegAN-CAT	BRATS2015, BRATS2019

Steps in the proposed methodology:

Preprocessing with LoG and CLAHE.

The image is smoothed after Laplacian of Gaussian (LoG) filtering removes noise and clutter.

To compute the LoG filter,

$$P(p,q) = \nabla^2 f(p,q) = \frac{\partial^2 f(p,q)}{\partial p^2} + \frac{\partial^2 f(p,q)}{\partial q^2}$$

Smoothed MRI images are then enhanced by CLAHE, which improves the contrast of each individual area of the image.Characteristic Extraction SGLDM provides accurate image classification (Spatial Gray Level Dependency Matrix). It aids the M-SVM technique. This uses six characteristics. Alternatively,

$$contrast = \sum_a \sum_b (a-b)^2 f(a,b)$$

$$mean = \sum_a \sum_b f(a,b)$$

$$variance = \sum_a \sum_b (1-mean)^2 f(a,b)$$

$$entropy = \sum_a \sum_b f(a,b) log\left(f(a,b)\right)$$

$$energy = \sum_a \sum_b f((a-b))^2$$

$$homogenity = \sum_{a,b} \frac{1}{1+(a-b)^2} f(a,b)$$

The co-occurrence matrix f(a,b) moves from pixel a to pixel b.

Algorithm:

1. Read the MRI images.
2. This option allows you to choose a specific window size for each pixel in a picture.

3. c. Select a pixels from the picture that is d pixels away and angled.

   The dimensions of the Matrix must be established.
4. SGLDM Matrix count can be substituted for the distance 'd' when the values of the specified pixel and the adjacent pixels are the same.

5. Steps B through E must be completed before Step 7 may be completed.

   M-SVM image classification.

31 The M-SVM employs the recovered features to diagnose MRI scans. Multi-class SVMs classify MRI images (M-SVM). During the trial, the classifier selects a category and calculates

$$b = argmax_{b'} \overline{w}^T \phi(\bar{a}, b)$$

During training, the margin between this value and the accurate class can form, hence quadratic programme equations are used.

$$\forall_i \forall_b \neq b_i \overline{w}^T \phi(\bar{a}_i , b_i) - \overline{w}^T \phi(\bar{a}_i , b_i) \geq 1 - \xi_i$$

6. MRI image segmentation using CNN.

Figure 4 depicts the kernel-based CNN approach used in this study. The MRI picture is first classified as normal or abnormal using M-SVM, and then a kernel-based CNN algorithm is used to identify any aberrant tissues or tumours in the patient. M-SVM, CNN, and the Kernel function are combined in this MRI image segmentation program to enhance performance and accuracy.

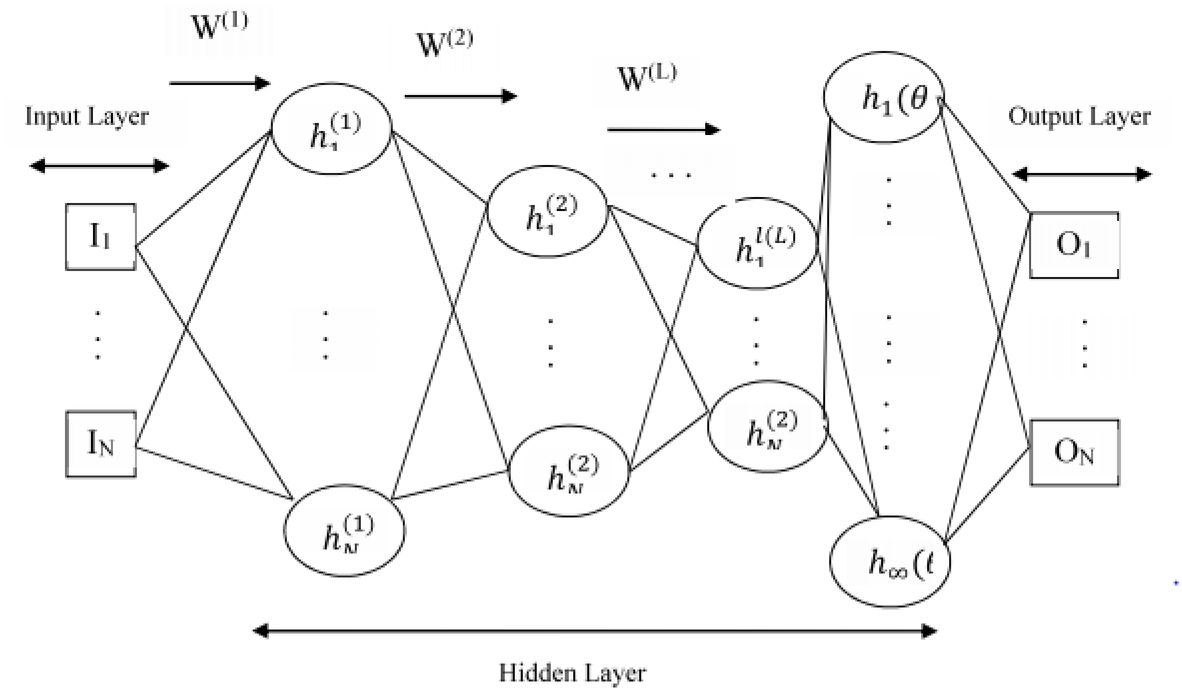

Figure 4: Kernel based CNN Architecture

6. Results and Discussions:

In this investigation, we used the Python Programming, Medical Segmentation Decathlon (MSD) [36] data set, in which we used Task01 BrainTumour as an example. All 750 have been categorised into two groups: Glioma (a necrotic/active tumour), and edoema (a swelling). It's a normal MRI scan that's taken in a hospital.

The planned work's performance was assessed using a variety of metrics. They are

Sensitivity = TP/TP+FN

Specificity= TN/TN+FP

Accuracy = TP+TN/TP+TN+FP+FN

Table 2: Analyses of Current and Future Work Performance

Measures	K-Means	SVM	CNN	Proposed Work
Sensitivity	84.6	83.1	89.4	95.3
Specificity	86.4	84.3	91.7	94.6
Accuracy	85.3	83.6	90.6	94.8

Error Rate: The percentage of patterns that a modeling approach erroneously classifies. Accompanying Figure 5 indicates the typical technique's error rate in comparison to the failure rate of current work..

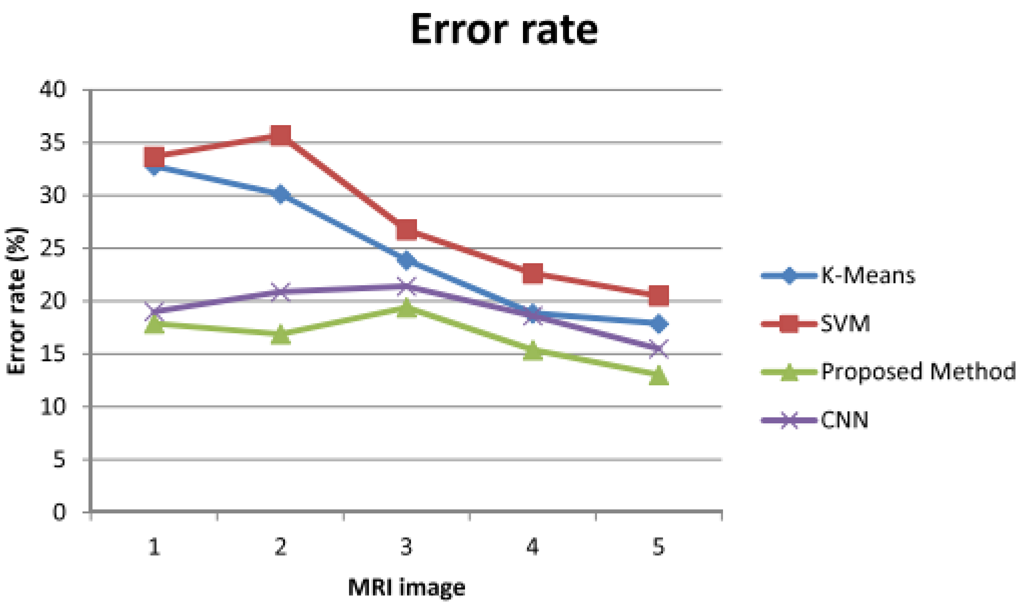

Figure 5: Ratio of proposed job errors to those of already completed work

7. Conclusions and Future Directions:

Even though medical image segmentation reached an advanced stage still its practical applications are limited. Due to current medical image segmentation research challenges: Cross-discipline medical picture segmentation combines both fields. Clinical pathology diseases can be complex and varied. But there's a dilemma with AI scientists and clinical needs: Doctors are unfamiliar with artificial intelligence and its workings. Thus, AI cannot satisfy specific clinical needs. Clinicians and AI researchers must collaborate more regularly to enhance medical AI. For the first time, machine learning researchers will have access to medical data. Deep learning researchers can utilise this data to design algorithms that are more clinically relevant.

Medical photographs and natural photos are vastly different. Medical images show differences. This mismatch affects the deep learning model's segmentation adaptability. In preparing medical photographs, noise and artefacts must be considered.

There are flaws in existing medical imaging data sets. Minimal medical imaging data sets. Due to the large amount of data sets required to train deep learning systems, overfitting occurs. Difficulty in deep Limited training data can be overcome via geometric modifications and colour space augmentation.

A flaw in deep learning. Design of networks, 3D segmentation models, and loss functions are all explored. It's worth studying the network's architecture. Changing the network structure has a large impact and is easily transferable. However, when 3D medical data is divided into individual slices, it loses some of the geometric information. As a result, developing 3D convolution models for medical imaging data processing is a potential research area. Loss function design has been a long-standing issue in deep learning. Deep learning has excelled at medical picture segmentation. New approaches are constantly improving segmentation accuracy and resilience. Artificial intelligence can help identify and treat a wide range of illnesses. Clinicians can benefit from it. It's still an open question, therefore new advances and research discoveries are likely in the coming years.

References

1. Lateef, F.; Ruichek, Y. Survey on semantic segmentation using deep learning techniques. Neurocomputing 2019, 338, 321–348. [CrossRef]
2. .Shen, D.; Wu, G.; Suk, H.I. Deep learning in medical image analysis. Annu. Rev. Biomed. Eng. 2017, 19, 221–248. [CrossRef]

3. Goodfellow, I.; Bengio, Y.; Courville, A.; Bengio, Y. Deep Learning; MIT Press: Cambridge, UK, 2016.
4. . Almeida, G.; Tavares, J.M.R.S. Deep learning in radiation oncology treatment planning for prostate cancer: A systematic review. J. Med. Syst. 2020, 44, 1–15. [CrossRef]
5. Hesamian, M.H.; Jia, W.; He, X.; Kennedy, P. Deep learning techniques for medical image segmentation: Achievements and challenges. J. Digit. Imaging 2019, 32, 582–596. [CrossRef] [PubMed]
6. . Altaf, F.; Islam, S.M.S.; Akhtar, N.; Nanjua, N.K. Going deep in medical image analysis: Concepts, methods, challenges, and future directions. IEEE Access 2019, 7, 99540–99572. [CrossRef]
7. Hu, P.; Cao, Y.; Wang, W.; Wei, B. Computer Assisted Three-Dimensional Reconstruction for Laparoscopic Resection in Adult Teratoma. J. Med. Imaging Health Inform. 2019, 9, 956–961. [CrossRef]
8. . Ess, A.; Müller, T.; Grabner, H.; Van Gool, L. Segmentation-Based Urban Traffic Scene Understanding. BMVC 2009, 1, 2.
9. . Geiger, A.; Lenz, P.; Urtasun, R. Are we ready for autonomous driving? The kitti vision benchmark suite. In Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition, Providence, RI, USA, 16–12 June 2012; pp. 3354–3361.
10. . Ma, Z.; Tavares, J.M.R.S.; Jorge, R.M.N. A review on the current segmentation algorithms for medical images. In Proceedings of the 1st International Conference on Imaging Theory and Applications, Lisbon, Portugal, 5–8 February 2009.
11. . Ferreira, A.; Gentil, F.; Tavares, J.M.R.S. Segmentation algorithms for ear image data towards biomechanical studies. Comput. Methods Biomech. Biomed. Eng. 2014, 17, 888–904. [CrossRef]
12. . Ma, Z.; Tavares, J.M.R.S.; Jorge, R.N.; Mascarenhas, T. A review of algorithms for medical image segmentation and their applications to the female pelvic cavity. Comput. Methods Biomech. Biomed. Eng. 2010, 13, 235–246. [CrossRef]
13. Xu, A.; Wang, L.; Feng, S.; Qu, Y. Threshold-based level set method of image segmentation. In Proceedings of the Third International Conference on Intelligent Networks and Intelligent Systems, Shenyang, China, 1–3 November 2010; pp. 703–706.
14. Cigla, C.; Alatan, A.A. Region-based image segmentation via graph cuts. In Proceedings of the 2008 15th IEEE International Conference on Image Processing, San Diego, CA, USA, 12–15 October 2008; pp. 2272–2275.
15. Yu-Qian, Z.; Wei-Hua, G.; Zhen-Cheng, C.; Tang, J.-T.; Li, L.-Y. Medical images edge detection based on mathematical morphology. In Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference, Shanghai, China, 17–18 January 2006; pp. 6492–6495.
16. He, K.; Gkioxari, G.; Dollár, P.; Girschik, R. Mask r-cnn. In Proceedings of the IEEE International Conference on Computer Vision, Venice, Italy, 22–29 October 2017; pp. 2961–2969.
17. Lin, G.; Milan, A.; Shen, C.; Reid, I. Refinenet: Multi-path refinement networks for high-resolution semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 1925–1934.
18. Noh, H.; Hong, S.; Han, B. Learning deconvolution network for semantic segmentation. In Proceedings of the IEEE International Conference on Computer Vision, Las Condes, Chile, 11–18 December 2015; pp. 1520–1528.
19. Gu, J.; Wang, Z.; Kuen, J.; Ma, L.; Shshroudy, A.; Shuai, B.; Liu, I.; Wang, X.; Wang, G.; Cai, J.; et al. Recent advances in convolutional neural networks. Pattern Recognit. 2018, 77, 354–377. [CrossRef]
20. Hubel, D.H.; Wiesel, T.N. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. J. Physiol. 1962, 160, 106. [CrossRef] [PubMed]
21. Fukushima, K.; Miyake, S. Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition. In Competition and Cooperation in Neural Nets; Springer: Berlin, Germany, 1982; pp. 267–285.
22. Lécun, Y.; Bottou, L.; Bengio, Y.; Haffner, P. Gradient-based learning applied to document recognition. IEEE 1998, 86, 2278–2324. [CrossRef]
23. . Krizhevsky, A.; Sutskever, I.; Hinton, G.E. Imagenet classification with deep convolutional neural networks. Adv. Neural Inf. Process. Syst. 2012, 60, 1097–1105. [CrossRef]
24. . He, K.; Zhang, X.; Ren, S.; Sun, J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 16 June–1 July 2016; pp. 770–778.
25. Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. arXiv 2014, arXiv:1409.1556.

26. Qiu, Z.; Yao, T.; Mei, T. Learning spatio-temporal representation with pseudo-3d residual networks. In Proceedings of the IEEE International Conference on Computer Vision, Venice, Italy, 22–29 October 2017; pp. 5533–5541.
27. Long, J.; Shelhamer, E.; Darrell, T. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 7–12 June 2015; pp. 3431–3440.
28. Myronenko, A. 3D MRI brain tumor segmentation using autoencoder regularization. In Proceedings of the International MICCAI Brainlesion Workshop, Shenzhen, China, 17 October 2018; pp. 311–320.
29. Nie, D.; Wang, L.; Adeli, E.; Lao, C.; Lin, W.; Shen, D. 3-D fully convolutional networks for multimodal isointense infant brain image segmentation. IEEE Trans. Cybern. 2019, 49, 1123–1136. [CrossRef] [PubMed]
30. Wang, S.; Yi, L.; Chen, Q.; Meng, Z.; Dong, H.; He, Z. Edge-aware Fully Convolutional Network with CRF-RNN Layer for Hippocampus Segmentation. In Proceedings of the 2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), Chongqing, China, 24–26 May 2019; pp. 803–806.
31. Borne, L.; Rivière, D.; Mangin, J.F. Combining 3D U-Net and bottom-up geometric constraints for automatic cortical sulci recognition. In Proceedings of the International Conference on Medical Imaging with Deep Learning, London, UK, 8–10 July 2019.
32. Casamitjana, A.; Catà, M.; Sánchez, I.; Combalia, M.; Vilaplana, V. Cascaded V-Net using ROI masks for brain tumor segmentation. In Proceedings of the International MICCAI Brainlesion Workshop, Quebec City, QC, Canada, 14 September 2017; pp. 381–391.
33. Moeskops, P.; Veta, M.; Lafarge, M.W.; Eppenhof, K.A.J.; Pluim, J.P.W. Adversarial training and dilated convolutions for brain MRI segmentation. In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support; Springer: Cham, Switzerland, 2017; pp. 56–64.
34. Rezaei, M.; Harmuth, K.; Gierke, W.; Kellermeier, T.; Fischer, M.; Yang, H.; Meinel, C. A conditional adversarial network for semantic segmentation of brain tumor. In Proceedings of the International MICCAI Brainlesion Workshop, Quebec City, QC, Canada, 14 September 2017; pp. 241–252.
35. Giacomello, E.; LoIacono, D.; Mainardi, L. Brain MRI Tumor Segmentation with Adversarial Networks. arXiv 2019, arXiv:1910.02717.
36. Simpson, A.L.; Antonelli, M.; Bakas, S.; Bilello, M.; Farahani, K.; Van Ginneken, B.; Kopp-Schneider, A.; Landman, B.A.; Litjens, G.; Menze, B.; et al. A large annotated medical image dataset for the development and evaluation of segmentation algorithms. arXiv 2019, arXiv:1902.09063