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A Survey on Applications and Performance of Deep Convolution Neural Network Architecture for Image Segmentation

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ABSTRACT

Image segmentation plays an important role in medical image processing and analysis. Proper analysis of medical images can improve the possible treatments and lead to survival rate of the patients. Image segmentation is a pre processing technique applied to the original images and splits the image into many meaningful structure or parts which are strongly correlated and is used for object representation, detection, recognition, measurement and visualization. Therefore, considering the importance and utility of the image segmentation, researchers are working in this field and resulted in extensive research and many approaches for image segmentation based on intensity, color, texture etc have been proposed. Several computational models based on supervised, unsupervised, parametric, probabilistic region based image segmentation techniques have been proposed. Recently, one of the machine learning technique known as, deep learning with convolution neural network has been widely used for development of efficient and automatic image segmentation models. In this paper, we focus on study of deep neural convolution network and its variants for automatic image segmentation rather than traditional image segmentation strategies. First, the state-of-the-art algorithms proposed on deep convolution network for medical image segmentation within the span of 2015 to 2017 has been studied, then the assessment of the current state with respect to the research challenges, objectives, performance and advantages and limitations along with the future scope of each proposed work has been addressed.

Keywords: Image segmentation; Medical Image Analysis; Deep Neural Network; Convolution Neural Network

1. OVERVIEW

Dividing an image into several meaningful structures or constituent regions or objects is known as *image segmentation*. This is basically an important pre processing step for image analysis which leads to object representation, detection, recognition, measurement and visualization and while partitioning an image into several distinct regions care should be taken to extract the objects or features of interest that correlate strongly [1-3]. Therefore, segmentation is also known as a mechanism of grouping pixels those shares similar attributes. Study reveals various kinds of image segmentation mechanisms. This image segmentation helps to process the low-level images to high-level ones. The success of image analysis is often based on success or failure of image segmentation. But, designing an accurate and reliable segmentation mechanism for image segmentation is thrust area for many of applications such as; industrial inspection, optical character recognition, object tracking, classification of satellite images, detection, recognition and measurement of bone, tissue in medical images [3-5]. The stopping criterion for image segmentation is when there is no object of interest with respect to the application is available. To separate an image into coherent groups or regions there are many traditional methods such as point, line, edge detection, thresholding, regions growing

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and morphological watershed and also few advanced methods such as clustering, model fitting and probabilistic methods are now under study [6-7]. Further, the categorization of image segmentation can be broadly classified into (a) *thresholding based segmentation*, in which histogram thresholding and slicing techniques are applied directly on the image and also can be combined with pre and post processing methods; (b) *edge based segmentation,* in which edges of the images are detected to identify the objects of interest; (c) *region based segmentation* approach starts to identify from the middle of the object and then grow outward to meet the boundary; (d) *clustering technique* is an exploratory data analysis of grouping high-dimensional data patterns of similar types and (e) *matching* is used to identify an approximately similar looking image to locate the object of interest in an image [1-5]. Image segmentation algorithms are basically based on discontinuity and similarity. The discontinuity based approach, partitions the image based on the abrupt changes in the intensity of the images and similarity based approach, partitions the image based on the similar type of regions based on some criteria such as thresholding, region growing, region splitting and merging [8]. This paper focuses on a thorough study on the medical image segmentation using a new variant of neural network called deep neural network or convolution neural network (CNN). In this study we have focussed on only the application of deep convolution neural network and its performance in image segmentation from literatures available during 2015 to 2017 only.

The rest of the paper has been organized as follows; section 2 depicts the some basic concepts of medical image segmentation with its requirement, section 3 describes the architecture and functionality of deep CNN along with the recent work done using deep CNN and its variants. A strong discussion with respect to challenges, issues observed on the deep CNN based image processing work studied in section 3 with its datasets, model adopted, performance and advantages and future scope of those works has been presented. Finally, Section 4 concludes the paper.

2. MEDICAL IMAGE SEGMENTATION

There are many applications of image segmentation in the medical field and has played an important role for automated detection of cancerous cells from mammographic images, Computed topography (CT) and Magnetic resonance (MR) imaging are the most widely used radiographic techniques in diagnosis, clinical studies and treatment planning [3-7]. Most medical images have poor noise-to-signal ratio than pictures taken in digital camera which leads to low spatial resolution and decreases the computational reliability. For example, the case of ultrasonic images, speckle noise reduces the ability of taking final decision in medical data analysis. Therefore, to obtain a clear image for proper verification and analysis from an image requires being pre processed and this is called as image segmentation, in which we try to obtain the pixels in the same class to have similar pixel values independent of their locations and the information gained from two image can be used to get proper integration of useful data from the image of interest [8]. There are many techniques available for diagnosis of brain tumor from the brain tissues, detection of brain tumor such as conventional radiology, ultrasonography, magnetic resonance imaging, computerized tomography and etc., but the process of diagnosing a number of CT-scan images manually becomes tiresome and also susceptible to error. Therefore, computer aided systems are used to assist the physicians as a second option to reduce the mistakes and errors, this raise the need of the automated computerised system. Therefore, to produce a reliable representation of brain-images, image segmentation as pre-processing task is require fro noise reduction, enhancement of image quality and clarity and this image segmentation as a pre processing task becomes the essential task in the field of medical image processing. For this image segmentation and further analysis many machine learning based techniques such as, *k*-mean, *k*-mediods, hierarchical and density based clustering techniques as well as artificial neural network with its many variants played a very significant role. Along with traditional neural network, recently many image segmentation works for medical image analysis has been done with promising results with respect to its computability and accuracy [9-10].

3. DEEP CONVOLUTION NEURAL NETWORK AND IT'S APPLICATION FOR IMAGE SEGMENTATION

CNN is comprised of one or more convolution layers followed by one or more fully connected layers, similar to neural network as shown in Figure 1. It consists of alternating convolution and pooling. In ordinary neural network each neurons of one layer connected with the neurons of another layer with a learnable weights and biases, where each neuron after receiving the inputs perform a dot products optionally followed by non-linearity. But CNN is a back propagation neural network having [11] weight kernels of two dimensions operate on images. It is having three layers, first one is *Convolution layer*, the second one is *Pooling layer* and the third one is *Fully-Connected layer*. The Network contains [12] set of layers, where each layer contains one or more planes. Basically it is explicitly assume that the inputs of CNN are images, hence the dimension of the input to the CNN layer is $m \times m \times r$ image which contains the raw pixel values of the image, where the height and width of the image is m and r is the number of channels. For example for an RGB image $r = 3$. The convolution layer is having k filters of size $n \times n \times p$, where n should be smaller than the image dimension and the size of p can either be same as r or can be smaller than r. This layer computes the output of neurons that are connected to local regions in the input. Then the element wise activation function is applied, such as $\max(o, x)$ thresholding at zero. At Pooling layer down sampling operations along with spatial dimensions (*widt*, *eig t*,) is performed, resulting the volume with less no of dimensions. And finally fully connected layer computes the class scores. This is the way how convolution transforms the original image layer to the final class scores. CNN exploit the knowledge, that the [13] inputs arise from a spatial structure, it is not an independent element.

CNN proves outstanding performance in many of the areas, basically in medical data image [14], it carefully classify the suspect area in the diagnostic process of the second phase. In fact it is able to detect all most all disease patterns. CNN is easier to train as it is having very less number of parameters with fewer connections, but despite of its relative efficiency of their local architecture, it shows expensive to apply in large scale for high resolution images. Deep CNN is capable of solving this problem [15] by using a highly optimized Graphics Processing Unit execution of 2D convolution and all other operations natural in training CNN.

Recently, the focus of ANN researchers have been shifted to deep learning, which is a class of ANN computing models and it learns from a hierarchy of high level features built from the lower level ones. These types of models are also known as CNN which automates the process of feature construction and involves both linear and on-linear data to learn and build the automated model from high level information

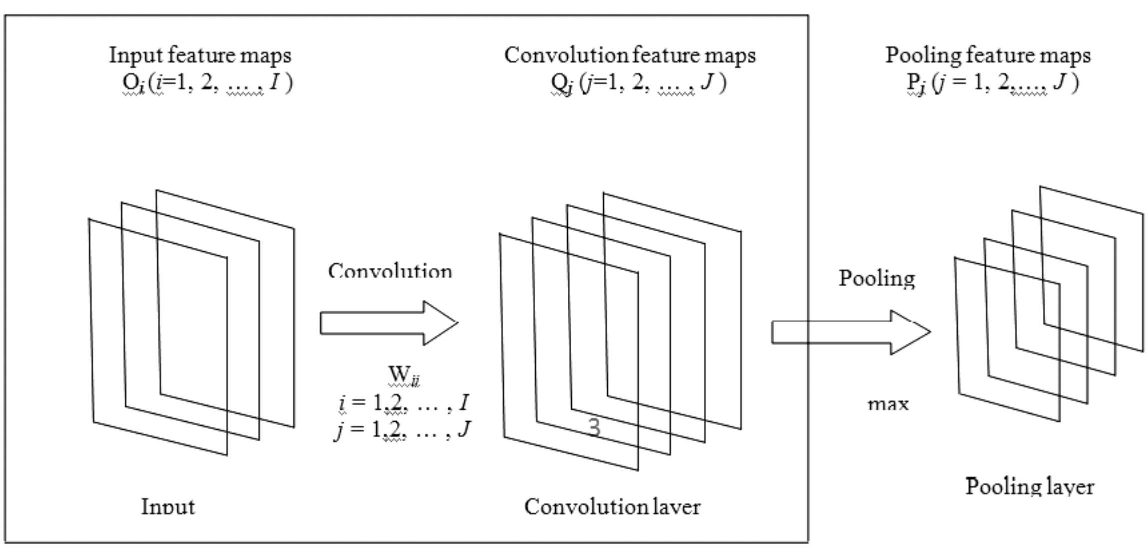

Figure 1: Structure of Convolution Neural Network (CNN)

from the low level information [16-32]. Considering the computational capabilities of CNN, Xiaohong W. Gao *et al.* [16] proposed a non-supervised automatic model to classify CT brain images for diagnosing it into having Alzheimer's disease (AD) or not. Three classes of CT images were first clustered into AD, lesion (tumour) and normal and advanced CNN architecture integrating 2D and 3D CNN has been proposed. The fusion of this CNN model has reported the accuracy of 85.2%, 80% and 95.3% for the above mentioned three classes with an average accuracy of 87.6%. Another fused work on deep learning by Xiaohong W. Gao *et al.* [17] for classification of echocardiography has been proposed recently. They have proposed one hybridized network architecture with two CNNs along space and time directions both in spatial and temporal information fused to obtain classification scores from both networks. This spatial CNN work upon the normalized images to learn spatial information and pre-processing of the all the images are done in temporal CNN before traing/learning starts and finally, to get the velocity and acceleration of images, the optical flow has been applied two times.

Shuchao Pang *et al*. [18] proposed a computational model for image classification based on end-to-end classifier using domain transferred deep convolutional neural networks or CNN. The proposed domain transferred deep convolutional neural networks (DT-DCNN) showed significant increase in the accuracy while classifying the medical images with high precision. The new thought of the authors for simple data augmentation based on classification has improved the performance of this CNN based hybridised model. Cecilia S. Lee *et al*. [19] recently disseminated a report on application of deep neural network with machine learning strategies for automatic image analysis from electronic medical records. Authors explored the capabilities of deep learning to distinguish normal Optical coherence tomography images from patients with age-related macular degeneration. A new convolutional neural network for classification with weights initialized by Xavier algorithm has been proposed. Training has been performed on 100 batch size images with learning rate of 0.001 utilizing the stochastic gradient descent optimization in multiple iterations. The performance of the deep neural network model has been recorded on 500 iterations using cross validation with validation test. This network have identified the key areas of the Optical coherence tomography images and the testing can identify the potential features to distinguish AMD images from normal images.

Wei Shen *et al*. [20] investigated the classification of CT images using machine learning based architecture and coined as Multi-crop Convolutional Neural Network (MC-CNN) to automatically extract the suspicious information based on a n multi-crop pooling strategy which crops different regions from convolutional feature maps without using segmentation to produce multi-sale features and applied on computationally effective single network. The goal of this work was to discover a set of discriminative features from hierarchical neural network to capture the suspicious information. The main challenge addressed by the authors is to generate an image space including both the healthy tissues and specific suspicious nodules at different scales by exploring the capabilities of deep learning architecture in an integrated fashion named as MC-CNN.

An interesting work on breast cancer diagnosis in mammography using deep learning strategy has been proposed by John Arevalo *et al*. [21] which automatically mine the discriminative features for learning. The proposed deep leaning model is based on two phases, first the quality of image is enhanced by prepossessing the images and in second phase, a supervised training strategy has been employed to classify the images. In the pre-processing stage, the images are cropped, then it goes through data augmentation, global contrast and local contrast normalization and then the machine learns the discriminative features using deep learning based strategy or CNN.

Automatic tumor segmentation of CT images is also one the challenging issue observed by the researchers, because the tumors have large spatial and structural variability. To address this issue a recent work for CT image segmentation using multiple supervised fully CNN by Lin Huang *et al*. [22] has been proposed. This model also goes though two phases, consisting of pre-processing to lower the differences among the images and a three layer multi-scale feature learning approach to capture both the local and global image features. The pre-processing has been performed in two aspects such as image intensity normalization and locating the image on the area of interest. Then, fully CNN has been used to transform a pre-trained model into a fully convolution form, augment the image with skip architecture to obtain a segmented map. The quantitative comparison of the proposed model based on *Dice Similarity Coefficient* (DSC), *Average Sensitivity* (AS), *Average Hammoude Distance*(AHD) and *F1-measure* have been done. Jeremy Kawahara *et al*. [23] proposed a BrainNetCNN model based on convolution network to predict the neurodevelopment from Diffusion Tensor images (DTI) of infants between 7 to 46 weeks. Authors proposed an edge-to-edge, edge-to-node and node-to-graph convolution filters to extract the topological locality of the structural brain network. Each filter takes all feature maps from the previous layer as inputs and a feature map has been produced as outputs for the next layer. The edge-to-edge layer is like a simple layer on convolutional layer and it filters data locally. An edge-to-node filter uses adjacency matrix from each feature map and takes a weighted combination of the incoming and outgoing weights. The relatively large weights are called as strong feature. Similarly, node-to-graph layer reduced the dimensionality of the nodes to output a single scalar per output feature map and this filter summarizes the response from neighbouring edges into a set of node responses to get a single response from all the nodes in the graph. In this work, authors have successfully demonstrated the capability of proposed model to learn the multiple independent injury patters to brain networks by predicting the parameters of each instance using deep learning strategy.

The tumors can appear anywhere in the brain and can be of any kind, size, shape and contrast. Therefore, to address the segmentation of this brain images, recently machine learning techniques are being explored very well. Considering the capability of deep neural network or CNN Mohammad Havaei *et al*. [24] proposed a novel CNN architecture which exploits both local and global contextual features. Rather than a traditional CNN, they have used a final layer in a convolutional network. Their model works in two phase training process to handle the imbalance of tumor class labels. This model is a fully automatic and to segment a brain image, it takes between 25 seconds to 3 minutes. The proposed two-path architecture goes through two phase training procedure which better deals with label imbalance problem of data distributions. This proposed cascade architecture is efficient and its performance has been measured by DICE, Sensitivity and Specificity.

Wenlu Zhang *et al*. [25] proposed a deep CNN (Deep-CNN) to segment the infant brain images into white matter, gray matter and cerebrospinal fluid which plays important role to study the development in health and disease. Athors have proposed a deep CNN strategy to segment the isointense stage brain tissue using a type of multi-layer, fully trainable models that can capture highly nonlinear mappings between inputs and outputs. CNN with many hidden layers have been proposed and all the patches extracted have been studied and it has been found that patch from each extracted tissue is not balanced.

Deep CNN also plays an important role in Forensic Dentistry also. Yuma Mikia *et al*. [26] proposed a computational model based on Deep-CNN for dental identification, post-mortem dental findings and teeth conditions from a dental chart and such results can be used to record the dental data properly. In this study, authors used Deep-CNN to classify the tooth types on dental CT images. First, they have mined the regions of interest from CT images and those were used for training this network. Basically, authors have investigated the power of random sampling for both training and testing. AlexNet with 5 convolution layers, 3 pooling layers and full connection layers are used for computation. The initial hand cropped region of interest have different sizes, but for experimentation, those images were again automatically resized and randomly cropped and the result have been compared with four resizing mechanisms such as; crop, squash, fill and half crop half fill. The classification accuracy observed using data augmentation is 93.5%. Pavle Prentašic *et al*. [27]

used this Deep-CNN to study the complications of diabetics caused by diabetic retinopathy. Before using the Deep-CNN, a denoising technique called *total variation* has been applied on the fondus photographs to exclude noise levels. Then, a CNN consisting of sequence of convolutional, max pooling fully connected layers have been used which is a hierarchical feature extractor and uses raw pixel intensities of original image to create a new feature vector for classification.

Jun Xu *et al*. [28] worked on automatic Deep-CNN based feature learning algorithm for segmentation and classification of Epithelial and Stromal images of tissues in histological images. The Deep-CNN strategy proposed in this study consists of two alternating convolution layers, maxpooling, two connection layers and a final classification layer. To train this network, coarse-to-fine sweep approach has been applied to extract more fine tuned settings. LIBSVM (a class of SVN classifier) with *Gaussian Kernel* and 10-fold cross validation has been used. The proposed model has been compared with nine state of the art Deep-CNN based models and also the sensitivity analysis and AUC curves are used to establish the performance of the model. Xipeng Pana *et al*. [29] worked on the Deep-CNN for segmentation of nuclei in pathological images. This work progresses in three phases; first spars reconstruction has been used to remove the background form pathological reports, then in second phase; Deep-CNN with cascade of convolution networks trained with gradient descent has been applied for segmentation of cell nuclei from the background. The machine has been trained with input patches with their corresponding class labels form the randomly selected pathological images. This model has also been compared with existing few existing methodologies such as; Support Vector Machine, *k*-nearest neighbour and *k*-means.

Recently, a deep CNN named as DeepNAT has been for automatic segmentation of the neuroanatomy in T1-weighted magnetic resonance images has been proposed by Christian Wachingera *et al*. [30]. This proposed multitasking model not only predicts the center voxel of the batch but also considers neighbours. This study also addresses the mostly challenged class imbalance problem by arranging two hierarchical networks to separate foreground from the background and identifies brain structures on the foreground. This DeepNAT uses three convolutional layers with pooling, batch normalization, and non-linearities, followed by fully connected layers. Main contributions are; multi-tasking for simultaneous training, hierarchical segmentation to separate foreground and background and introduction of spectral coordinates as parameters to retain the context information in patches. Proposed DeepNAT has been compared with the state of the art two methods such as; PICSL and STAPLE

4. DISCUSSION/ RESEARCH CHALLENGES / OVERALLPERFORMANCE/ OBSERVATIONS

Researchers	*Datasets used*	*Techniques Applied*	*Overall Performance*	*Observations*
Xiaohong W. Gao *et al.*	285 datasets of 3D are collected from Navy General Hospital, China, which compose 57, 115 and 113 data respectively in the category of Alzheimer's, lesion and normal	Deep Neural Network/ CNN	The fusion of this CNN model has reported the accuracy of 85.2%, 80% and 95.3% respectively for AD lesion (tumour) and normal and advanced CNN architecture integrating 2D and 3D CNN	Application of deep learning neural network compromises with the largest number of datasets and also the data imbalance problem needs to be addressed and the better accuracy can be observed if we have more balanced data
Xiaohong W. Gao *et al.*	432 ultrasonic videos images of echocardiography from Tsinghua University Hospital at Beijing and Fuzhou University Hospital at Fuzhou, China. These data contain eight view classes captured from 93	Fused Deep Learning/ CNN	Without using acceleration of temporal information, proposed work outperforms all the hand-crafted approaches with 89.5% precision rate	This fused CNN/Deep network integrated model is both automatic and selective for classification of echocardiography images from videos and the proposed two-strand networks shows classification

(contd...Table)

Research-ers	*Datasets used*	*Techniques Applied*	*Overall Performance*	*Observations*
	patients aged between 7 and 85 years old comprising of 35 wall motion abnormalities and 58 normal cases			accuracy up to 92.1% and is the best so far the literature is concerned.
Shuchao Pang *et al*.	Three well-known public bio-medical image databases such as; NEMA-CT, TCIA-CT and OASIS-MRI database	Domain Transferred Deep Neural Network (DT-DCNN)	Proposed method obtained accuracy of 100 % for NEMA-CT and TIA-CT datasets and 93.76% for OASIS-MRI dataset	This method can effectively deal with a limited number of labelled biomedical images with deep learning and transfer learning
Cecilia S. Lee	2.6 million OCT images of 43 328 macular OCT scans from 9285 patients. After linking the macular OCT scans to the EMR, 48 312 images from 4392 normal OCT scans and 52 690 images from 4790 AMD OCT scans were selected. 80 839 images used for trailing and 20 163 images for testing or validation.	Deep Learning	Accuracy at image level, the ROC curve of 92.78% with an accuracy of 87.63%. At the macula level, ROC curve of 93.83% with an accuracy of 88.98%. At a patient level, ROC curve of 97.45% with an accuracy of 93.45%. Peak sensitivity and specificity with optimal cutoffs were 92.64% and 93.69%, respectively	The application of occlusion testing provides insight into the trained deep learning model and which features were most important in distinguishing AMD images from normal images. This study has included only images from patients who met author's study criteria, and the neural network was only trained on these images and they did not exclude images with poor quality
Wei Shen *et al*.	LIDC-IDRI dataset consisting of 1010 patients with lung cancer thoracic CT scans as well as mark-up annotated lesions	Multi-crop Convolutional Neural Network (MC-CNN)	Classification accuracy (87.14%) and the AUC score (0.93)	The extracted deep features from the proposed methodology can be considered to be integrated with conventional image features to further improve the precision performance
John Arevalo *et al*.	The datasets are extracted from Breast Cancer Digital Repository (BCDR). The dataset was built from 344 breast cancer patients' cases containing a total of 736 film mammography views with 426 benign lesions and 310 malignant lesions	CNN	The increasing the performance has been observed 0.826 in terms of AUC and the Wilcoxon test hypothesis evaluated rep-resents (K<0.1)	This model used a combination of image –based features with additional segmentation information and this combination improved the performance results especially it helps to augment the performance of the hand-crated representation.
Lin Huang *et al*.	405 test images (109 bone lesion osteosarcoma CT images and 296 mixed lesion osteos-arcoma CT images)	Fully CNN	DSC of 87.80%, AS of 86.88% HM of 19.81%, F1-measure of 0.9080	Limitations observed for segmentation of smaller tumor regions being not sensitive to the small details of images and the output contains some vague results due to the large up-sample stride. This can be handled by using more convolutional layers.
Jeremy Kawahara *et al*.	168 DTI images from a cohort of infants born very preterm and scanned between 27 and 45	BrainNet CNN	Absolute error of age predict-ion was correlated with r=0.224, implying that age predictions	Connections from the premotor and primary motor cortices were found to be predictive of

(contd...Table)

Researchers	*Datasets used*	*Techniques Applied*	*Overall Performance*	*Observations*
	weeks postmenstrual age		were more accurate for younger infants	better motor outcomes.
Havaei *et al*.	Fully-annotated MIC CAI brain tumor segmentation challenge 2013 dataset using the well defined training and testing splits	CNN-DNN	The time needed to segment an entire brain varies between 25 seconds and 3 minutes, making them practical segmentation methods	This method has been evaluated by BRATS 2013 online evaluation system and confirms its performance and the two-pathway model also achieves good result when the data distribution is unbalanced.
Wenlu Zhang *et al*.	Acquired T1, T2, and diffusion weighted MR images of 10 healthy infants using a Siemens 3T head only MR scanner	Deep-CNN	DICE ratio has been applied to quantitatively measure the segmentation accuracy and also the statistical significance has been performed using Wilcoxon signed rank tests	The strategy worked well to find the patches but it has been observed that, the number of patches are not imbalanced, which can be handled by sampling or ensemble learning strategies
Yuma Mikia *et al*.	Two dental CT units, namely Veraviewepocs 3D (J.Morita Mfg, Corp., Kyoto, Japan) and Alphard VEGA (Asahi Roentgen Ind. Co., Ltd., Kyoto, Japan), which were used to acquire images in 33 and 19 cases	Deep-CNN	Classification accuracy obtained 80% without segmentation and by increasing the number of training samples by rotation and intensity transformation accuracy of 91.0% was achieved	Deep learning in general is considered to require a large number of training samples but in this work, despite the limited number of cases, the promising accuracy has been observed. Due to convolution with the pooling process, this method is robust enough to automatically, shift the image, recognized and classify tooth type.
Pavle Prentašic *et al*.	DRiDB which contains 50 color fundus images for which all the main structures like blood vessels, optic disk and macula are marked along with pathological changes	Deep-CNN	For each image, the number of true positives (TP), false positives (FP) and false negatives (FN) are 0.78, 0.78 and 0.78 respectively.	Deep-CNN has been effectively used to segmentation in color fondus photographs and it has been observed that, this work can be enhanced by adding some more pre and post processing steps and also adding some high level features for final segmentation.
Jun Xu *et al*.	*Dataset I*: Netherlands Cancer Institute (NKI) and Vancouver General Hospital (VGH). It consists of 157 rectangular image regions (106 NKI, 51 VGH) *Dataset II*: Helsinki University Central Hospital from 1989 to 1998. D2 comprises 27 TMAs of colorectal cancer	Deep-CNN	This Deep-CNN based approach yields a perfect result (100%) in terms of True Positive Rate (TPR), True Negative Rate (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), Accuracy (ACC), F1 Score (F1), and Matthews Correlation Coefficient (MCC)	Proposed architecture uses a deep architecture to learn complex features in a data-driven fashion and it has shown improved classification accuracy obtained via handcrafted features.
Xipeng Pana *et al*.	58 Hematoxylin and Eosin (H&E) histopathology images of breast tissue from Yale,	Deep-CNN	Accuracy (ACC), precision (P), recall (R), and F1-measure (F1) are adopted as the performance	First, the sparse reconstruction with K-SVD and Batch-OMP algorithms are used to enhance

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Research-ers	Datasets used	Techniques Applied	Overall Performance	Observations
	David Rimm's Laboratory, with 32 benign and 26 malignant images respectively. http://medicine.yale.edu/bbs/ molecularcell/people/david_rimm.profile		metrics and also three commonly used segmentation methods such as; OTSU, FCM based and Watershed-based were applied to the dataset to produce the baseline performances for comparison purposes	the nucleus area and remove background and then, the segmentation has been gone using Deep-CNN with structural labels and finally, morphological operations with some prior knowledge has been introduced to improve the segmentation performance
Christian Wachingera *et al*.	MICCAI MultiAtlas Labeling challenge1 (Landman and Warfield, 2012), which consists of T1-weighted MRI scans from 30 subjects of OASIS	DeepNAT	DeepNATcrf yields significantly higher DICE scores in comparison to DeepNAT (p < 0.00 1), FreeSurfer (p < 0.00 1), and STAPLE (p < 0.00 1), whereas the diffierence to PICSL (p=0.06) is not significant.	Authors proposed a 3D Deep-CNN for segmentation of MRI scans. It evolved through three main phases such as; multi-task learning, hierarchical segmentation, spectral coordinates, and 3D fully connected conditional random field. Further thisi work can be improved by increasing the amount of training data, progresses in GPU and also structural and methodological advances in deep CNN.

5. CONCLUSION

Automatic segmentation of CT images, ultrasonic videos images of echocardiography, OCT images, brain tumor for cancer diagnosis is a challenging task for the computer scientist. There are many publicly available datasets are provided for the researchers to experiment, develop and evaluate their proposed models for image segmentation. This paper initially sketches the basic concepts of medical image processing. We have specifically tried to understand the deep convolution neural network and its applications in image segmentation for medical images only and also our focus is only the recent work done in this filed from 2015 to 2017. Medical image processing has a significant growth in development of new technologies and still a lot research is left unattended and will definitely encourage the researches to explore new technologies for proper identification, detection, diagnosis and exploration of images for medical field.

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