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A Comparison of Deep Learning Neural Networks for Image Processing Applications

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ABSTRACT

Currently segmentation of images with complex structure is a tedious process. To overcome this complexity image processing is combined with neural networks. In neural networks, convolutional networks have recently overcome many problems in image processing and also proves its effectiveness in various areas namely image recognition and classification. This paper deals with various existing works on deep convolutional networks based on different types of images which include both medical and non medical images respectively. So the main idea behind the paper is to focus on the literature survey of various existing applications of deep convolutional networks and also the merits and demerits of the papers for further enhancement and accuracy.

***Keywords* :-** Segmentation, Deep Convolutional Neural Networks, Pap smear.

I. INTRODUCTION

A deep convolutional network is a kind of fully connected network where the connection between the neurons is based on the organization of animal visual cortex and mainly used for classifying images. So this deep convolutional networks acts as the state of the art for complex image processing. The four main operations in convolutional neural networks are as follows

- Convolution
- Non Linearity
- Pooling or Sub Sampling
- Classification

The name itself says that there will be many networks in depth. Since it as depth characteristic deep networks acts better than fully connected network by handling many features of the complex images in detail. The fully connected networks have some following disadvantages

- Overfitting problem may occur and requirement of memory for weights may lead to hardware implementation problem.
- The topology of the input has been not totally unnoticed.

The various layers of the deep convolutional networks are shown in Fig. 1.

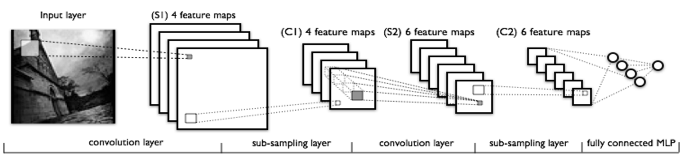

Fig. 1 Convolutional neural network for processing image

This paper has four sections. Sections 2 deals with various applications of deep convolutional networks are given in the form of survey. The merits and demerits in the existing work are discussed in the section 3. Section 4 provides the conclusion to the paper. This section also says about the future work.

II. LITERATURE SURVEY

Nasrollahi *et al.* [1] proposed the action recognition based on deep convolutional networks, where the idea is based on converting low resolution videos to high resolution videos so that the action of the object in the videos can be easily detected. This is done by giving low resolution video as an input and it is upgraded by bicubic interpolation and deep learning based super resolution algorithm in parallel. And then the output is blended by alpha blending using alpha value as 0.2 Given a set of high resolution images and corresponding low resolution images the mean square error is calculated and it is minimized using gradient descent with standard backpropagation. So this overcomes the problem of dense trajectories to work with low resolution videos.

Ciresan *et al.* [2] proposed to recognize hand written Chinese character based on multi-column deep networks. This paper totally based on to bring high recognition rate for detecting Chinese character when compared to ICDAR 2011 and 2013 using multi-column deep networks. This works only on the already preprocessed data. Since it works on Chinese characters the preprocessing is hard limited the image to fixed size and contrast maximization. It gives 1.01% rate reduction of absolute error for ICDAR 2013 and 3.6% for ICDAR 2011.

Goodfellow *et al.* [3] proposed to recognize multi digit number using deep convolutional neural network. Here with high resolution street view imagery with multi digit number the deep convolutional networks are trained to recognize the digits in an organize manner without cropping it. It uses SVHN dataset and the performance rate is directly proportional to the depth of the layer. This was also used in reCAPTCHA images and got an accuracy of 99.8% respectively.

Papandreou *et al.* [4] proposed semantic image segmentation using weakly and semi-supervised learning of deep convolutional network. In this paper deep convolutional neural network with a fully conditional random field is combined to do segmentation of semantic image with high resolution. Expectation-Maximization methods were used to train the deep convolutional semantic segment model from weakly annotated data. When smaller number of pixel level images is combined to larger number of pixel level the performance is excellent.

Ran *et al.* [5] proposed the semantic image segmentation using nonlocal convolutional networks. The main idea behind semantic segmentation is object detection. Here, at first input image is enhanced by applying normalization and then 3 convolutional layer of one local (stride 1) and two non local (stride 3, stride 5) were added in parallel. At then it is ended with convolutional layer which is used for combining the feature maps of local and non local layer.

Ahranjany *et al.* [6] proposed the hand written Fassi/Arabic digits using convolutional neural networks. It is preprocessed by eliminating the pixels that belongs to the marginal area and then the size is normalized. In normalization step the character were first centered using centroid shift procedure and converted into binary image by Otsu thresholding. At last convolutional neural network of 8 layer depth is applied where 2 layer is for sub sampling and 2 convolutional layer, followed by two fully connected layer for non linear classification and one output and input layer. The accuracy of 99.17% was obtained and when digits that are hard to recognize is rejected the accuracy of 99.98% is obtained.

Zhang *et al.* [7] used multi task deep neural networks for multiview face recognition. Here the author applied deep convolutional neural network post filter for automatic extraction of features. Multitask learning were used for estimation of facial pose and facial landmark localization which improves the accuracy.

Kale *et al.* [8] proposed the cervical cell segmentation by two phase using Herlev and Hacettepe data set. It also segments the cells that are single and overlapped. In the first phase using multiscale watershed segmentation, the regions are extracted and a hierarchical tree is build using hierarchical segmentation algorithm. Later only the meaningful regions are selected from the tree. In the second phase using the segments obtained from the first phase it is classified as nucleus or cytoplasm with the help of SVM with a radial basis Kernal function.

Bergmeir *et al.* [9] proposed the segmentation of high-resolution microscopic cervical nuclei images. Here using canny edge detection algorithm relevant edges are detected, from which nuclei is extracted later. But before applying canny edge a median filter of size 5x5 is applied on the mean shift filtered images, to smooth the curvature. Now based on the assumption that nuclei are elliptical in shape, a randomized Hough transform is applied to locate the nuclei.

Li *et al.* [10] proposed the segmentation of cervical cell based on Radiating GVF Snake method. It works on Herlev dataset. Main aim is to extraction of both the nucleus and cytoplasm from a single cell cervical smear image. First the image is converted to CIELAB color space and the L* dimension is normalized to form grayscale image. The non-local mean filter is used to remove the noises. A spatial K-means clustering algorithm is used to extract the initial contours of the nucleus and cytoplasm. With the above initial contours RGVF is performed which includes stack refinement and a new edge based computation for detecting the nucleus and cytoplasm boundaries respectively.

Genctav *et al.* [11] proposed segmentation Pap smear cells segmentation in a unsupervised manner The process is done in two stages. In the first stage the cell image is divided based on homogeneity and circularity by multi-scale hierarchical segmentation. The second stage is used for classifying the nucleus and cytoplasm with the help of binary classifier.

Zhang *et al.* [12] proposed segmentation of abnormal cells using global and local graph cuts. At first the image contrast is enhanced by extracting A* channel, so that the cells are brighter than the background. Linear stretch and median filter are applied to enhance the contrast and remove noises. The cervical cell is separated from the background by Otsu multiple thresholding algorithm. The segments obtained by Otsu method is further refined by multiway graph cut approach. By this way cytoplasm is segmented. Using adaptive thresholding algorithm the nucleus region is approximately detected and then it is further refined within its local neighbourhood by using poison distribution based graph cut. The overlapping cells are segmented based on combining two concave points.

Cengizler *et al.* [13] proposed cervical cell segmentation based on fluid dynamics based deformable model. Here fluid dynamics based simulation engine gives the perfect fluid behavioral pattern. In this approach the cell clusters are extracted first. Then using gradient magnitude as the source the particles are extracted. Finally the virtual fluid is passed to the extracted particles. The flow of the fluid around the object boundaries is based on the fluid interaction with the particles. Based on this boundary the cell is segmented. This approach is more adaptive when compared to watershed algorithm.

Chankong *et al.* [14] proposed the segmentation of nucleus and cytoplasm by fuzzy C-means clustering method. First the input image is converted into grayscale and a median filter is applied to discard the noise. By using FCM clustering method the image is classified into 3 areas namely nucleus, cytoplasm and background. At last it is differentiated into nucleus if the center value is less than the threshold value of nucleus and it is named as cytoplasm if the center value is between nucleus and cytoplasm threshold value.

Guan *et al.* [15] proposed accurate segmentation of cervical cells that are partially overlapped using GVF snake model and dynamic contour searching. It addresses the problem of partially overlapping cells segmentation in high resolution images. It is based on three assumptions namely the nucleus is surrounded by set of contour points, only the subset of these contour points are used and at last it is divided into strong and weak contour points. The first step is to extract nucleus in the image and then by setting nucleus as center the original image is cropped. Finally all the extraction are combined. Finally the DSCS algorithm with the GVF snake model is combined to extract accurate cell contour.

Song *et al.* [16] proposed segmentation using deep learning. In this approach the image is preprocessed for removing Gaussian noises by applying trimmed mean filter. Next the template is created to provide rough cytoplasmic region by segmenting the image coarsely so that it would reduce the computational time for superpixel extraction. Based on 18 color features the CNN method is applied to segment nuclei region using Sobel edge operator and an adaptive thresholding algorithm. The segmented nucleus is further segmented to get a perfect result.

Song *et al.* [17] proposed cervical cytoplasm and nuclei segmentation using Multiscale Convolutional Network (MSCN) and graph partitioning. Here deep learning based MSCN method is used for initial segmentation cells and using multiscale feature vectors the nucleus region is detected. And then it is fine segmented to get accurate result. When compared to raw pixel segmentation, superpixel segmentation of cytoplasm and nucleus gives an improved accuracy of 5.06% and 2.06%.

The merits and demerits of deep convolutional neural network in non-medical and medical images are discussed in table 1 and table 2 respectively

TABLE 1

REVIEW OF SEGMENTATION OF NON-MEDICAL IMAGES WITH DEEP LEARNING

Authors	Merits	Remarks
K.Nasrollahi, S.Escalera, P.Rasti, G.Anbarjafari, X.Baro,H.J.Escalante, T.B.Moeslund, [2015][1]	The combination of super resolution algorithm and bicubic interpolation with alpha blending gives a high resolution images.	—
D.Ciresan, U.Meier[2015][2]	It gives 1.01% rate reduction of absolute error for ICDAR 2013 and 3.6% for ICDAR 2011.	Training a bigdata of Chinese characters is a too slow task and decreases performance efficiency. It works only on preprocessed data.
I.J.Goodfellow, Y.Bulatov, J.Ibarz,S.Arnoud,V.Shet [2014] [3]	The digits are recognized in a better manner and for reCAPTCHA it gots an accuracy of 99.8%	For large number of character length it doesn't provide a better result, so it is not applicable for it.
G.Papandreou, L.Chieh Chen, K.P.Murphy, A.L.Yuille [2015] [4]	When smaller number of pixel level images is combined to larger number of pixel level the performance is excellent.	Weak annotation alone was insufficient to train high quality segmentation model.
L.Ran, Y.Zhang,G.Hua [2015] [5]	Even on the large environment it is able to sample the input image and gets an accuracy of 54.7%	The performance efficiency can be increased.
S. S. Ahranjany, F.Razzazi [2010] [6]	By applying convolutional neural network it as obtained the accuracy of 99.17% and when digits that are hard to recognize is rejected the accuracy of 99.98% is obtained.	The network can be further trained to detect the digits that are hard to recognize with improved accuracy.
C.Zhang and Z. Zhang [2014][7]	By combining deep convolutional neural network and multitask learning in FDDB dataset, the detection rate is improved by 3%.	It can be further improved by applying many other attributes which would increase the performance

TABLE 2

REVIEW OF SEGMENTATION OF MEDICAL IMAGES

Authors	Merits	Remarks
A.Kale, S.Aksoy [2010][8]	It is generic to handle both single cell and overlapping cells. Using multi-scale watershed segmentation algorithm meaningful regions are segmented.	It can be improved by adding some more features like size to the first phase for better result.
C.Bergmeir, M.G.Silvente,J.M.Benitez [2011] [9]	Based on the assumption that shape of the nucleus surrounded by cytoplasm is elliptical. A randomized Hough transform is used to detect the nucleus which would give effective result.	It works based on assumption only. The nucleus can be overlapped with each other which may cause change in shape. So if the shape changes from ellipse this cannot be applicable.
K. Li, Z. Lu, W. Liu, and J. Yin [2012][10]	The problem caused by the inflammatory cells is reduced. The obscure boundaries are located.	Cannot handle the overlapping images.
A. Gençtav, S. Aksoy, and S. Önder[2012] [11]	Segmentation of cervical cell in overlapping images was accurate	The accuracy of overall performance can be further enhanced. It doesn't deal with columnar cells.
L.Zing, H.Kong, C.T.Chin, S.Liu, T.Wang, S.Chen [2014][12]	Delineation when imaging conditions are not ideal. The LAGC approach and concave points method enable segmentation of overlapping nuclei.	The boundary of cytoplasm for each cell is not outlined.
C.Cengizler, M.Guven, M..Avei[2014][13]	Produce better result on the automated images. More suitable task for automatic segmentation. Better than Watershed-based segmentation	Fluid leakage from the cell walls.
T. Chankong, N. Theera-Umpon, and S. Auephanwiriyakul [2014][14]	Obtained the accuracies of 93.78% for 7 class and 99.27% for 2 class problems.	It is not used for cervical cell image with multiple cells.
T. Guan, D. Zhou, and Y. Liu [2015][15]	The process is totally automatic and it can segment the partially overlapped cell.	It is not applicable for two or more overlapping cells.
Y.Song, L.Zhang, S.Chen, B.Li, Y.Zhou, B.Lei, T.Wang [2015][16]	Both superpixel extraction and CNN method are effective way to segment the cervical cancer	It doesn't deal with overlapping of cells.
Y.Song, L.Zhang, S.chen, D.Ni, B.Lei, T.Wang [2016] [17]	The superpixel, graph partitioning and MSCN are extremely efficient for segmenting cervical cell. It provides a powerful support for automatic screening and detection of cervical cancer.	It is not applicable for splitting overlapping cytoplasm. Atrophic cell are inaccurately segmented. Splitting performance is degraded for nucleus that is overlapped with complex shapes.

III. CONCLUSIONS

The merits and demerits of the existing work have been discussed thoroughly. Each work has its own ups and downs. Therefore segmentation of complex image is a challenging process in the computer world. When compared to others, deeplearning based object detection and segmentation would give better results. So the deeplearning based approach can be further extended to higher levels for recognition of handwritten tamil characters.

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