International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

AUTOMATED CERVICAL CANCER SCREENING USING TRANSFER LEARNING

Navdeep Kaur[1], Nikson Panigrahi[2], Ajay Mittal[3]

[1]*Department of Computer Science & Applications, MCM DAV College for Women, Chandigarh, India*

[2,3]*Department of Computer Science & Engineering, UIET, Panjab University, Chandigarh, India*

ABSTRACT

Colposcopy is an important diagnostic method for detecting cervical cancer. It is a clinical method, in which ace-to-whitening effect i.e. the different degree of whiteness after application of acetic acid solution is observed to determine the abnormal tissues. As this method is dependent on expertise of colposcopists, it is the high demand for developing computer aided solution for cervical cancer detection. In this work, a type of Deep Convolution Neural Network based on transfer learning is presented to automatically detect cervical cancer on the basis of type of transformation zone. First of all, irrelevant information from image has been removed. Secondly, method of Data Augmentation has been used to enlarge the dataset. Thirdly, transfer learning is used to transfer the pre-trained Very deep convolution network (VGG16/19) over ImageNet, for feature extraction. Lastly, fully connected neural classifier has been presented to classify the image into three types.

Keywords- Transformation zone, deep convolution neural network, neural network, transfer learning, data augmentation

I. INTRODUCTION

Cervical cancer, also known as uterine cancer, is considered as the fourth most common disease worldwide [1], and has increased the death rate as hasty level. Most of the cervix cancer cases are preventable if diagnosed in early stages, by routine screening. Pap smear is the most common test used for cervical cancer screening but it is not a diagnostic test, it require further testing series e.g. Colposcopy, biopsy, endocervical scraping and cone biopsies. Following an abnormal Pap smear test, colposcopy is the important diagnostic method used to detect this disease. Although final diagnosis must be made on histopathological examination, colposcopy helps in reducing over treatment, determining abnormal cervical lesions, directing biopsy and in determining the location for biopsies.

Most of the cervical cancer patients' go untreated due to lack of appropriate treatment. The precise positioning and visibility of tranzformation zone (TZ) is the key to optimized judgement of treatment. The appropriate treatment can be judged with the determination of type of patient's transformation zone. On the basis of size, visibility and location, International Federation for Colposcopy and Cervical Pathology [2] has classified TZ into three types: Type1, Type2 and Type3. This need experienced colposcopists for determination of patient's TZ types visually, which is not available everywhere especially in rural areas, so it suffer from human error. Therefore, computer aided diagnosis techniques will help to determine TZ type effectively and facilitate doctors in deciding appropriate treatment accordingly.

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

In this work, we aim to create a deep convolutional neural network- based system to classify the colposcopy images into three types of transformation zones. Due to limited dataset, we used the concept of transfer learning [3] and used pretrained VGG16/VGG19 over ImageNet [4] and presented the classifier with three fully connected layers. The outlline of this paper is organized as follows: Section 2 gives an overview of the various stages involved in computer aided cervical cancer detection. Our proposed method is explained in Section 3. Further results are shown and compared in Section 4. Section 5 presents the conclusion and future scope of the problem.

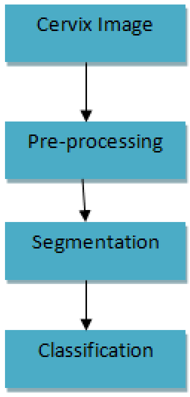


Fig. 1: Layout of CAD Scheme

II. RELATED WORK

Computer Aided Diagnosis (CAD) applications have proven to be of great importance in detection of malignancy for tumors [5, 6, 7]. Especially, Deep learning has achieved great success in the field of image classification. In the past, several methods have been proposed to detect and classify cervical dysplasia.

The process of detecting cervical cancer from colposcopic images involves three main steps (Fig. 1): Pre-processing, Segmentation and Feature Extraction, Classification. The role of pre-processing is to remove noise and enhance the image quality before segmenting it into various regions discriminating the portion to be analysed from the background. Further, in classification step, different regions are classified into benign and malicious regions. All the three steps have been summarized in TABLE II.

2.1. Pre-processing- Although colposcopy images are captured in a fixed position, quality of images is inferior due to the following reasons: i) Random movements- The continuous cervix movement due to breathe or other physiological conditions or light sources are addressed by image enhancement techniques i.e. contrast, brightness, scaling, zooming etc. ii) Specular reflection- the fluid present in cervix acts like a mirror and creates specular reflection, G. Zimmerman and H. Greenspan[8] detected specular reflection utilizing image intensity, saturation, and gradient information; whereas, Abhishek Das, Avijit Kar have used the dilated feature for detection [9]; whereas Mingpei Liang removed it using bi-linear interpolation and . iii) Region of interest- The irrelevant information e.g. Hair, clinical instruments etc present in colposcopic image can mislead the CAD system, so Region of interest can be detected either by color features [10, 11], or by Gaussian Mixture Model[12] iv) Blood vessels- Green filters are used to visualize the blood vessels better [13]

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

2.2 Image Segmentation- The main goal of image segmentation is to partition the image into meaningful objects, so as to analyze the abnormal portions efficiently. Traditionally, on the basis of mathematical tools used image segmentation methods are classified into six classes: Thresholding, Region based, Clustering, Edge based, Fuzzy based, Neural based. The different segmentation techniques used for cervical cancer detection have been listed in TABLE I.

TABLE I: SUMMARY OF SEGMENTATION TECHNIQUES USED IN COLPOSCOPY IMAGES

Technique	Description	References
Thresholding	It is based on histograms.	[25]
Region based segmentation	It start from middle and grow till object boundaries are detected	[20]
Clustering	It groups together similar patterns	[18] [21] [22][12]
Edge based segmentation	Boundaries are detected and objects are identified by filling the boundaries	[9]
Fuzzy based	Based on multidimensional rules derived from fuzzy logic	[24]
Neural based	Process small areas using ANN	[23]

2.3 Classification- The features extracted from the segmented regions are used to classify the cervix images into benign and malicious regions. To understand the relationship between data and the classes, classification techniques include two types of learning process: supervised and unsupervised learning. Due to the availability of domain knowledge, supervised classifiers generally outperform the unsupervised classifiers where numerical exploration is required for data analysis. In past, several supervised classifier including nearest neighbour, Bayesian classifier, SVM, ANN classifier and unsupervised classifiers including k-means, fuzzy clustering, have been reported for classification of cervix images.

TABLE II: SUMMARY OF VARIOUS STEPS INVOLVED IN CAD OF CERIVCAL CANCER

Algorithm	Pre Processing	Segmentation/Feature Extraction	Classification
Tulpule, B. et.al [18]	-	K means	-
Gordon, S., Zimmerman, G.[12]	Irrelevant information like instruments etc and specular reflections using GMM	Gaussian Mixture Model	GMM
Huang, X.[19]		SVM	
SAMYA MUHURI et. al[20]	Noise removal using low filter Image ehancement using Gabor filter	Marker Control Watershed segmentation.	SVM

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Zhang, S[21]	NIL	K-SVD	SVM
Hernández-lemus, E[22]	Green filters Area based image registration method	PLA, PSA	kNN, NB and C4.5
Simões, P. W.[23]	Contrast enhancement	-	hybrid neural network based on Kohonen self-organizing maps and MLP networks
Van Raad,[8]	Low pass filter and down sampling	MAP color based segmentation	Piece wise curve characterisation using frequency descriptors and ellipse fitting
Mingpei Liang [9]	Specular reflection removed using Bi-linear interpolation	Edge based segmentation	SVM

III. PROPOSED METHOD

3.1 Data: We have used the cervix images from the database released as part of Kaggle competition [14], which contains images for three types of cervix images i.e. Type 1, Type 2 and Type 3. The database has been released in two stages; original dataset consists of 249 images for Type 1, 781 images for Type 2 and 450 images of Type 3 constituting a total of 1480 images. The other dataset being the additional dataset consists of 1187 images of Type 1, 639 images of Type 2, 1972 images of Type 3, constituting a total of 3798 images. . Initially, the model was trained using original dataset as well as additional dataset. But, upon looking onto the images and training VGG16 net we have found that the additional dataset only results in poor training of the network as noise level is high in additional dataset.

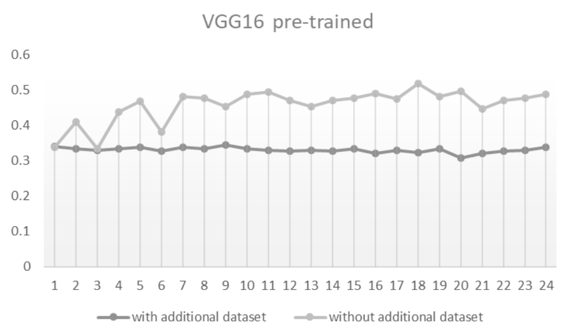


Fig. 2: Accuracy vs epochs for VGG16-pre-trained with and without additional dataset

Thus, we only used original dataset for training purpose. The distribution of dataset is summarized in TABLE III; 20% of the original dataset has been chosen as validation dataset and rest for training.

TABLE III: DISTRIBUTION OF DATASET FOR TRAINING AND VALIDATION

Cervix Type	Type 1	Type 2	Type 3
Train	199	617	356

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Validation	50	155	89

3.2 Experimentation: Due to limited dataset, instead of training a Convolutional Neural Network (CNN) from scratch, we finalized the approach of transfer learning [3]. The implementation is done using Keras Platform with tensorflow backend and trained on NVIDIA Titan Xp 12GB GPU with 12 GB of RAM. Keras is a high level neural network API written in Python, capable of running over theano, tensorflow and CNTK. In this work, we have used two variants of VGG16 and VGG19 for experimentation and then comparative results has been presented in section 4.

The detailed proposed architecture as shown in Fig. 3, consist of 4 steps: First, cropping the images focusing on cervix part; Second, dataset enhancement using data augmentation at run-time; Third, Feature extraction using VGG16/19; Fourth, Classification on the basis of features extracted from the model.

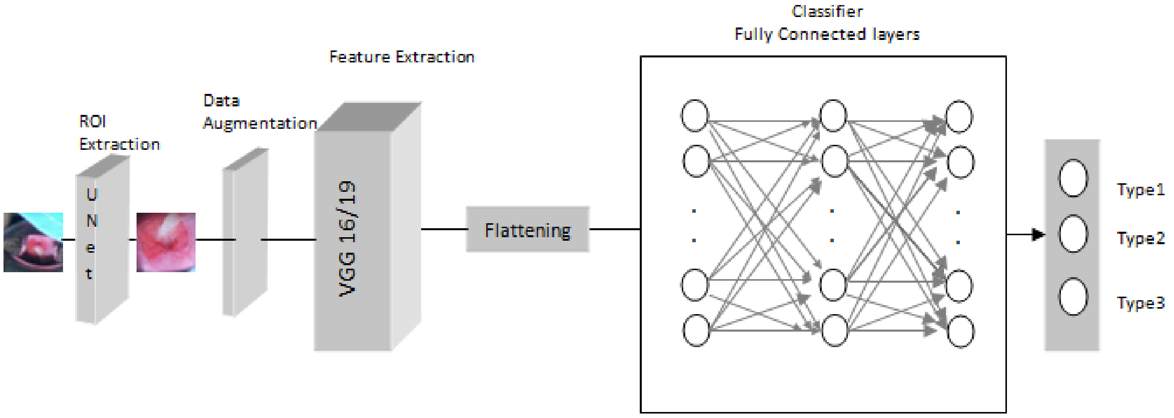


Fig. 3: Proposed Architecture

STEP 1: Region of Interest: The cervix region occupies more than half of the image, rest is the irrelevant information e.g. equipments, non cervix tissues etc. Thus, the region of interest (ROI) has been detected using U-Net [15] and the irrelevant information has been cropped from the images as in Fig. 5.

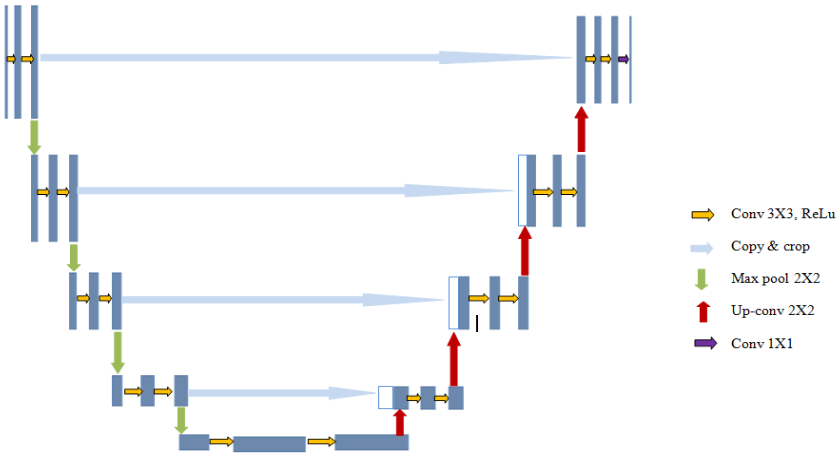
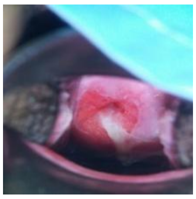


Fig. 4: Architecture of U-Net [15]

U-Net is a network used for pixel-wise predictions. Its uniqueness is because in it feature maps from convolution part in downsampling step are fed to upsampling step; which facilitate it to use original features as well for predictions, resulting in high performance. The detailed architecture of U-Net is described in Fig. 4.



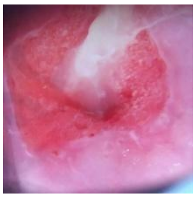


Fig. 5 a) Original Image b) After extracting ROI

STEP 2: Data Augmentation: Due to limited dataset, several data augmentation techniques has been applied to reduce over fitting and improve the generalization of the model. After extracting ROI, the dataset has been transformed using scaling, shifting, zooming, shearing and rotating each image with a random degree from -10^{o} to 10^{o}. This data transformation is a runtime process, resulting in less memory and high computational speed and increasing the training dataset by 6- folds.

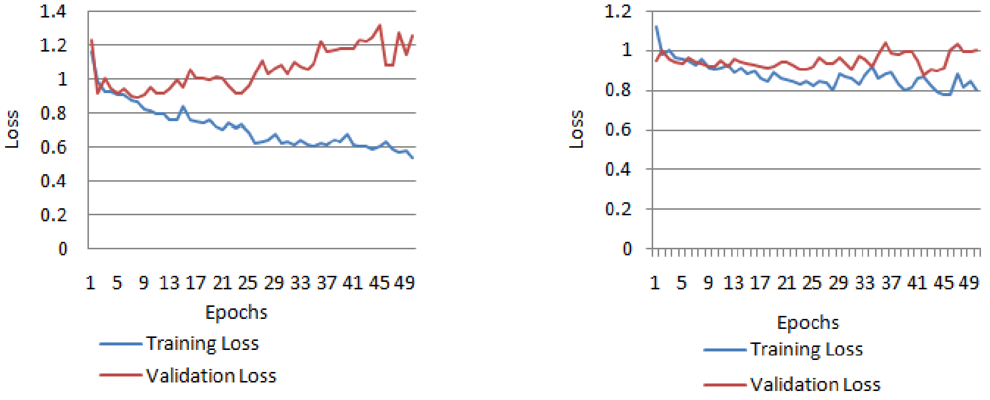
TABLE IV: No of Input/ Output for layers of the proposed classifier

Layer	**Input**	**Output**
Flattening	4X4X512	8192
First Fully Connected layer	8192	512
Second Fully Connected layer	512	256
Third Fully Connected layer	256	3

STEP 3: Feature Extraction: Very deep convolution network , Visual Geometry Group,VGG16/19 [16], pre-trained over ImageNet database containing million of images, is chosen due to its ease of implementation and its success in ILSVRC 2013 competition. The model is imported from keras library for extracting feature of the images in the convolutional layers of the VGG16/VGG19.

STEP 4: Classification: The features extracted from VGG16 has been flattened and fed to the proposed classifier. The proposed classifier is a neural network consisting of three fully connected layers with dropout of 0.2. The input and output for each fully connected layer and flattening is summarized in TABLE IV. Dropout is the most common regularization technique proposed by Srivastava et.al [17] for training deep models; in which some neurons are randomly set to inactive modes during training in each forward step, resulting in generalized trained model. Another regularization method, “early stopping” has also been implemented and the training has been stopped as soon as the validation performance starts to saturate or deteriorate.

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

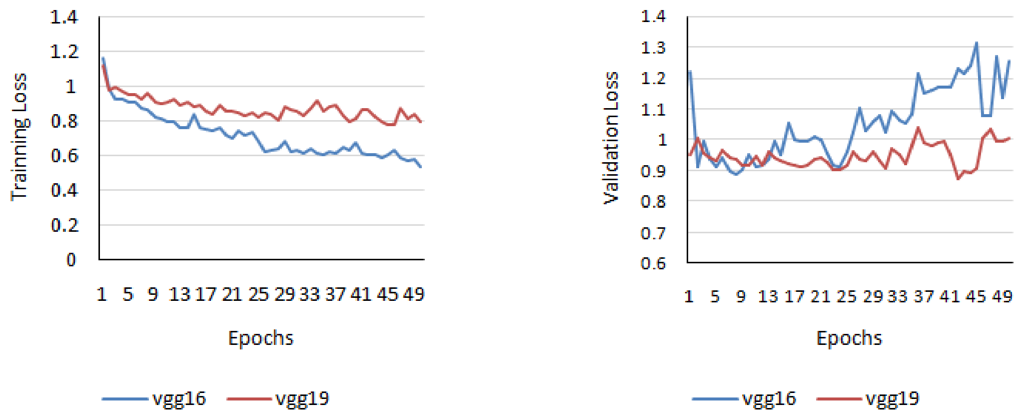


a b

Fig. 6: Summary of training and **validation** loss vs epochs a) VGG16 b)VGG19

IV. RESULTS

To validate the learning process, the loss has been plotted wrt epochs i.e. the number of times the training set is traversed. In Fig. 6, it has been observed that validation loss is higher than training loss in VGG16 with significant difference; resulting in overfitting. The overfitting is caused by training the data with on a limited dataset for a longer period of time. The more the model gets trained on specific set of images the more it gets over-fitted. Whereas, for VGG16 validation loss is slightly greater than training loss; resulting in good fit.



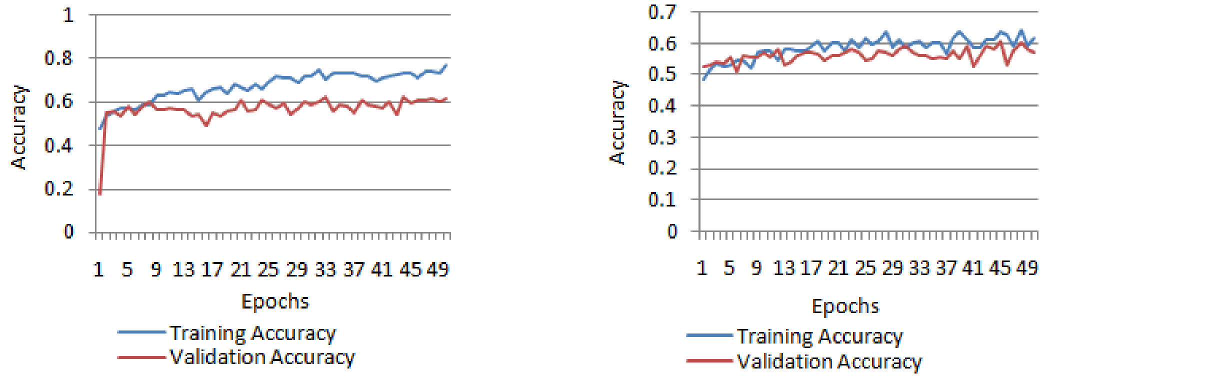
a b

Fig. 7: a) Training Loss vs Epochs for VGG16 and VGG19 b) Validation Loss vs Epochs for VGG16 and VGG19

In Fig. 7, the training loss curve decrease with considerable rate at the start, whereas normalizing afterwards; showing good learning rate.

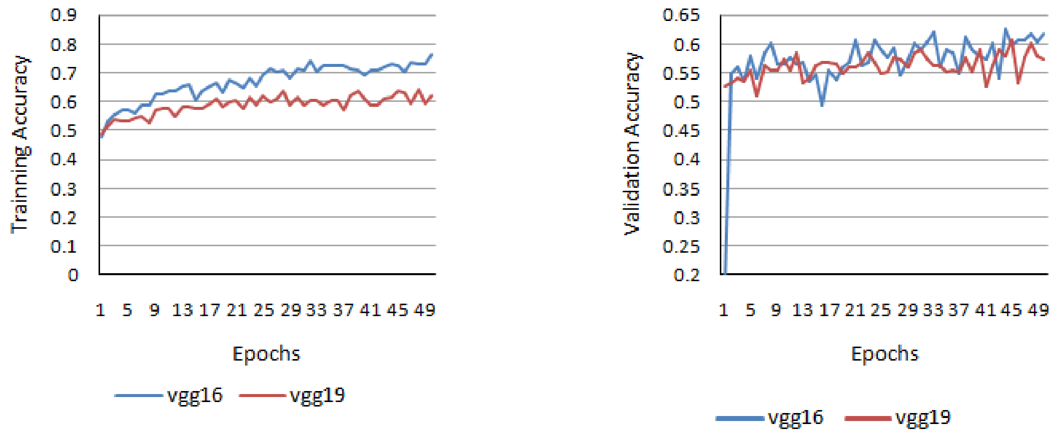
In addition to loss, accuracy has been monitored wrt epochs (Fig. 8). In Fig. 9, it is observed that validation accuracy curve is increasing and has achieved accuracy of 0.621528 and 0.607639 for VGG16 and VGG19 respectively.

International Journal of Advance Research in Science and Engineering
Vol. No.6, Issue No. 08, August 2017
www.ijarse.com
IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346



a b

Fig. 8: Accuracy wrt epochs a) VGG16 b) VGG19



a **b**

Fig. 9: a) Training Loss wrt epochs of VGG16 and VGG19

b) Validation Loss wrt Epochs of VGG16 and VGG19.

The training accuracy for VGG16 is higher than VGG19 as shown in Fig.9. Since, both the networks only differ in the feature extraction mechanism, the accuracy curve depicts that VGG16 is capable of better selection of features required by the classifier than VGG19; resulting in better training of the network classifier. However both the models achieve almost similar validation accuracy, VGG16 has achieved maximum validation accuracy than VGG19; making it better candidate than VGG19.

V. CONCLUSION AND FUTURE SCOPE

In this paper, we presented deep neural network based algorithm for cervical TZ type classification, so that appropriate treatment can be provided to cervical cancer patients. The proposed system extracted region of interest by removing the irrelevant information from images using U-Net; using transfer learning; the performance has been improved through testing various pre-processing techniques and implementing classifier with varied layer and drop out and best results are presented here i.e. 3 fully connected layers with dropout 0.2. Although the proposed system has achieved good accuracy, even then the model is overfitted. Thus, in future the focus will be on finding better accuracy models that can remove the overconfident predictions.The colposcopic images are often of lower quality due to specular reflection; also bleeding clots mislead the CAD system, thus, in future we plan to reduce these noises.

REFERENCES

[1] McGuire, Shelley, World cancer report 2014. Geneva, Switzerland: World Health Organization, international agency for research on cancer, WHO Press, 2015, *Advances in Nutrition: An International Review Journal 7.2 ,2016: 418-419*.

[2] Walker P, Dexeus S, De Paol G *et al.,* International Federation for Cervical Pathology and Colposcopy Nomenclature Committee, *Obstet Gynecol 2003; 101*:175–7.

[3] Oquab M, Bottou L, Laptev I, et al., Learning and Transferring Mid-level Image Representations Using Convolutional Neural Networks, *IEEE Conference on Computer Vision and Pattern Recognition (CVPR). USA: IEEE Computer Society, 2014*, pp 1717-1724

[4] DENG J, DONG W, SOCHER R, et al., ImageNet: a large-scale hierarchical image database, C. Proceedings of the 2009, *IEEE Conference on Computer Vision and Pattern Recognition. Washington, DC: IEEE Computer Society, 2009*, pp 248-255.

[5] Giger M. L., Chan H.-P. & Boone J., Anniversary paper: history and status of CAD and quantitative image analysis: the role of medical physics and AAPM, *Med. Phys. 35, 2008*, pp 5799–5820.

[6] Cheng, J. Z., Chou, Y. H., Huang, C. S., Chang, Y. C., Tiu, C. M., Chen, K. W., & Chen, C. M., Computer-aided US diagnosis of breast lesions by using cell-based contour grouping, *Radiology 255, 2010*, pp 746–754.

[7] Way T. W. *et al.*, Computer-aided diagnosis of pulmonary nodules on CT scans: improvement of classification performance with nodule surface features, *Med. Phys. 36, 2009,* pp 3086–3098.

[8] Van Raad, V., Xue, Z., & Lange, H.,Lesion Margin Analysis for Automated Classification of Cervical Cancer Lesions, *Proc. of SPIE Medical Imaging, 2006, 6144, 3*. https://doi.org/10.1117/12.651119

[9] Liang, M.,Identification of Abnormal Cervical Regions from Colposcopy Image Sequences, *21st International Conference on Computer Graphics, Visualization and Computer Vision 2013*, pp 130–136.

[10] Zimmerman-Moreno, Gali, and Hayit Greenspan, Automatic detection of specular reflections in uterine cervix images, *Medical Imaging, 6144.1*, 2006.

[11] Raad, V. Van, Image Analysis and Segmentation of Anatomical Features of Cervix Uteri in Color Space, *STI Medical Systems, 2005* , pp. 2–5.

[12] Gordon, S., Zimmerman, G., Long, R., Antani, S., Jeronimo, J., and Greenspan, H.,Content analysis of uterine cervix images: Initial steps towards content based indexing and retrieval of cervigrams, *SPIE, Medical Imaging: Image Processing, 2006*, pp 2037–2045.

[13] Balas, Costas, A novel optical imaging method for the early detection, quantitative grading, and mapping of cancerous and precancerous lesions of cervix, *IEEE Transactions on biomedical engineering, 2001, 48.1,* pp 96-104.

[14] Intel & MobileODT Challenge on Cervical Cancer on Kaggle 2017. https://www.kaggle.com/c/intel-mobileodt-cervical-cancer-screening. Last accessed on August 1, 2017.

[15] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox, U-net: Convolutional networks for biomedical image segmentation, *International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer International Publishing, 2015.*

[16] Simonyan, Karen, and Andrew Zisserman, Very deep convolutional networks for large-scale image recognition, *arXiv* preprint arXiv: 1409.1556, 2014.

[17] Srivastava, Nitish, et al., Dropout: a simple way to prevent neural networks from overfitting., *Journal of machine learning research 15.1, 2014,* pp 1929-1958.

[18] Tulpule, B., Hernes, D., Srinivasan, Y., Yang, S., Mitra, S., Sriraja, Y., Nutter, B., Phillips, B., Long, L., and Ferris, D., A probabilistic approach to segmentation and classification of neoplasia in uterine cervix images using color and geometric features, *SPIE, Medical Imaging: Image Processing, 2005*, 995–1003.

[19] Huang, X.,Wang, W., Xue, Z., Antani, S., Long, L. R., and Jeronimo, J.,Tissue classification using cluster features for lesion detection in digital cervigrams, *SPIE, Medical Imaging: Image Processing, 2008*.

[20] SAMYA MUHURI, M. B., Automated Identification & Analysis of Cervical Cancer, *3rd World Conference on Applied Sciences, Engineering and Technology 27-29 September 2014, Kathmandu, Nepal*, ISBN 13: 978-81-930222-0-7, pp 516-520.

[21] Zhang, S., Huang, J., Wang, W., Huang, X., & Metaxas, D., Cervigram image segmentation based on reconstructive sparse representations, *SPIE Medical Imaging 2010: Image Processing, 2010*. https://doi.org/10.1117/12.845461.

[22] Guti´, K., errez-Fragoso, H G Acosta-Mesa, N. C.-R., R, I., Hern´, Andez-Jim´, & Enez., Automatic classification of acetowhite temporal patterns to identify precursor lesions of cervical cancer, *Journal of Physics: Conference Series 475 (2013) 012004, 2013* https://doi.org/10.1088/1742-6596/475/1/012004.

[23] Simões, P. W., Izumi, N. B., Casagrande, R. S., Venson, R., Veronezi, C. D., Moretti, G. P., … Manenti, S. A. (2014).,Classification of Images Acquired with Colposcopy Using Artificial Neural Networks, *Cancer Informatics, 2014,* pp 119–124. https://doi.org/10.4137/CIN.S17948.

[24] Bhakti Tulpule, Shuyu Yang, Yeshwanth Srinivasan, Sunanda Mitra, and Brian Nutter, Segmentation and Classification of Cervix Lesions by Pattern and Texture Analysis, *The 14th IEEE International Conference on Fuzzy Systems, 2005. FUZZ '05, at Reno, NV, USA, 25 May 2005*, pp 173-176, Print ISSN: 1098-7584

[25] Rama Praba, P.S. and H. Ranganathan, WAVELET TRANSFORM BASED AUTOMATIC LESION DETECTION IN CERVIX IMAGES USING ACTIVE CONTOUR, *Journal of Computer Science, 2013, pp 30-36 ISSN 1549-3636*, doi:10.3844/jcssp.2013.30.36 Published Online 9 (1) 2013