An Analysis of Convolutional Neural Networks for Cervix Type Colposcopy Image Classification

N Thendral
Assistant Professor
Department of Electronics and Communication Engineering, Meenakshi College of Engineering, Chennai, Tamilnadu, India

D Lakshmi
Associate Professor
Department of Electronics and Communication Engineering, St. Joseph's College of Engineering, Chennai, Tamilnadu, India

B Senthil Kumar
Associate Professor
Department of Electronics and Instrumentation Engineering, St. Joseph's College of Engineering, Chennai, Tamilnadu, India

T Subhashini, D Jeevitha, M Logeswari
UG Scholar
Department of Electronics and Communication Engineering, Meenakshi College of Engineering, Chennai, Tamilnadu, India

Abstract **- Cervical cancer is the second most occurring cancer in women of all age groups. It causes cells on the cervix to grow out of control. Cervical cancer is caused by a virus called human papillomavirus (HPV). In the early stages of cancer, there will be very little symptoms which make it difficult to detect. If cancer is detected at an early stage, then proper and effective medication can be started at the right time. Usual methods available for detection of cervical cancer largely depend on human expertise. With the advancements in medical imaging technology, computerized methods were also developed to detect the cancerous cells at an early stage. The type of treatment for cervical cancer is primarily determined by the cervix type of the patient and hence its type detection is very important. Thus, we have proposed a method to classify the cervix type using deep learning technology. A Region based Convolutional Neural Network (R-CNN) model is created and compared with the basic Convolutional Neural Network (CNN). From the experimental results, a validation accuracy of is 91% achieved.**

Keywords **- Cervical Cancer, Deep Learning, Colposcopy, R-CNN, Medical Image Classification.**

I. INTRODUCTION

Cervical cancer leads to the fourth highest number of deaths in female cancers, carrying high risks of morbidity and mortality [1]. Nevertheless, the cervical cancer is slow growing, so its progression through precancerous changes provides opportunities for prevention, early detection, and treatment. To this end, in 2018, the Director-General of the World Health Organization (WHO) announced a global call to action towards the elimination of cervical cancer. The main challenge of cervical cancer elimination centres on the low- and middle- income countries (LMICs) where gender discrimination and extreme poverty severely limit a woman‘s choice to seek care resulting in over 88% of deaths from cervical cancer.

Currently, there are several screening tools, including cervical cytology (Pap tests) and human papillomavirus (HPV) test, for cervical cancer by detecting the cervical intraepithelial neoplasia (CIN), which potentially is the precancerous change and abnormal growth of squamous cells on the surface of the cervix [2]. The cervical cytology requires experienced cytologists to handle the microscopy, which is unattainable in lower source settings.

The HPV test has been recommended as an alternative to the traditional cytology screening without presence of skilled cytologists. However, the high false positive rate of HPV screening increases Cytogists. However, the high false positive rate of HPV screening increases the workload of the following colposcopy examination.

Due to the lack of well-trained colposcopists, thorough and precise colposcopy examinations are not widespread in LMIC. Colposcopy establishes a bridge between the screening and diagnosis of cervical cancer that differentiating the false positives from the previous screening approaches and provides guidance (the location and severity of lesions). The colposcopy with biopsy is one of most commonly- used approaches for the diagnosis of CIN and cervical cancer.

WHO divided the CIN into three grades namely Type 1 (CIN1), Type 2(CIN2) and Type 3 (CIN 3), which can be categorized to low-grade (Type 1) and high-grade (Type 2/3) squamous intraepithelial lesions respectively. If a patient potentially having low-grade squamous intraepithelial lesions or worse is identified by the colposcopist, a colposcopy directed biopsy is required to perform for the confirmation.

In this paper, we proposed an automatic method for classification of cervix type colposcopy images using deep learning. This classify the cervix images into type 1, type 2 and type 3 based on the transformation zone [3].

We have used the cervix images from the database released as part of Kaggle competition [4], 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. We only used original dataset for training purpose. 20% of the original dataset has been chosen as test dataset and rest for training. All the calculations, arithmetic units role is essential. [6-8].

II. RELATED WORK

Anas et al [5] proposed a Neural Network (NN) based system for classifying cervical cells as normal, low-grade squamous intra-epithelial lesion (LSIL) and high-grade squamous intra-epithelial lesion (HSIL). The system consists of three stages. In the first stage, cervical cells are segmented using the Adaptive Fuzzy Moving K-means (AFMKM) clustering algorithm. In the second stage, the feature extraction process is performed. In the third stage, the extracted data is classified using Fuzzy Min-Max (FMM) NN.

Navdeep et al [6] presented a type of Deep Convolution Neural Network based on transfer learning 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.

Thendral et al [7] proposed a method for automatic cervical cancer detection using segmentation and classification. In this work, several methods used for detecting cervical cancer is discussed which uses different classification techniques like *K*-means clustering, texture classification and Support Vector Machine (SVM) to detect cervical cancer. The proposed work compares and determines accuracy for five types of kernel functions, namely Polynomial kernel, Quadratic kernel, RBF kernel, linear kernel, and Multi-Layer Perceptron kernel. Analysis shows that Multi-layer Perceptron kernel in SVM classifier provides the best performance compared to others.

Jack et al [8] created a deep learning model to classify cervix types in order to help healthcare providers provide better care to women all over the world. Classification of medical images is known to be a difficult problem for a number of reasons, but recent advancements in Deep Learning techniques have shown promise for such tasks. They experimented with a number of convolutional architectures before settling on residual neural networks with dropout and batch normalization to produces scores for each class, with loss calculated based on the multi-class logarithmic loss. Through experimentation, they found that it is indeed very difficult for train a model from scratch that is general enough to solve this problem.

Zhang et al [9] presented a study used a deep learning model to classify the images of cervical lesions. Clinicians could determine patient treatment based on the type of cervix, which greatly improved the diagnostic efficiency and accuracy. The study was divided into two parts. First, convolutional neural networks were used to segment the lesions in the cervical images; and second, a neural network model similar to CapsNet was used to identify and classify the cervical images.

III. METHODOLOGY

A. Region Based Convolutional Neural Network

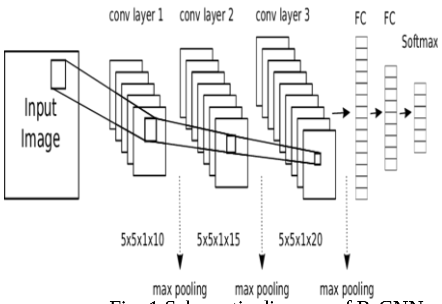


Fig. 1 Schematic diagram of R-CNN

The deep learning approach, regions with convolutional neural networks (R-CNN) shown in figure 1, combines rectangular region proposals with convolutional neural network features. It is used for finding and classifying objects in an image. R-CNN is a two-stage detection algorithm. The first stage identifies a subset of regions in an image that might contain an object. The second stage classifies the object in each region. The *R-CNN* first extracts many region proposals from the input image, labeling their classes and bounding boxes.

Then a CNN is used to perform forward propagation on each region proposal to extract its features. Next, features of each region proposal are used for predicting the class and bounding box of this region proposal. Models for image classification using regions with CNNs are performed based on three processes. First find regions in the image that might contain an object. These regions are called region proposals. Then extract CNN features from the region proposals. Finally classify the objects using the extracted features.

The R-CNN consists of four steps. (i) Perform selective search to extract multiple high-quality region proposals on the input image. These proposed regions are usually selected at multiple scales with different shapes and sizes. Each region proposal will be labeled with a class and a ground-truth bounding box.

(ii) Choose a pretrained CNN and truncate it before the output layer. Resize each region proposal to the input size required by the network, and output the extracted features for the region proposal through forward propagation. (iii) Take the extracted features and labeled class of each region proposal as an example. Train multiple support vector machines to classify objects, where each support vector machine individually determines whether the example contains a specific class. (iv) Take the extracted features and labeled bounding box of each region proposal as an example and train a linear regression model to predict the ground-truth bounding box.

B. Convolutional Neural Network (CNN)

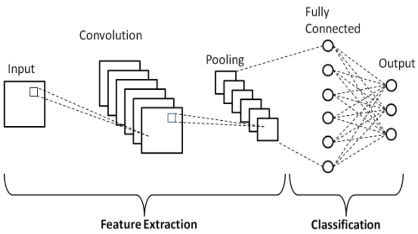


Fig. 2 Schematic diagram of basic CNN

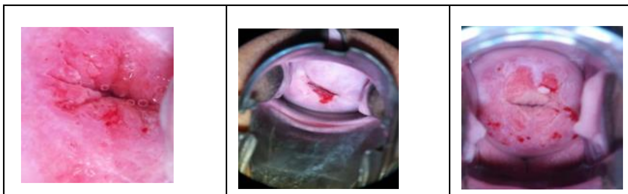
Figure 2 shows the basic CNN model. Convolution is the first layer to extract features for an input image. Convolution preserves the relationship between pixels by learning image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel. A Pooling layers is an another building block of a CNN. Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. Pooling layer operates on each features map independently.

Fully connected layers are an essential component of Convolution Neural Network (CNN), which have been proven very successful in recognizing and classifying images for computer vision. The CNN process begins with convolution and pooling, Breaking down the images into features and analysing them independently. The output layer in a CNN as mentioned previously is a fully connected layer, where the input from the other layers is flattened and sent so as the transform the output into the number of classes as desired by the network.

IV. RESULTS AND DISCUSSION

The type 1, type 2 and type 3 test images are shown in figure 3. Figure 4 shows the training and validation accuracy and figure 5 depicts the training and test loss of the R-CNN model. Figure 6 presents the training and validation accuracy and figure 7 shows the training and test loss of the basic CNN model. [10-12].

The overall performance metrics are shown in table I and the class wise metrics are depicted in table II.



(a) Type 1 (b) Type 2 (c) Type 3

Fig. 3 Test Images

Fig. 5 Model Accuracy of R-CNN model

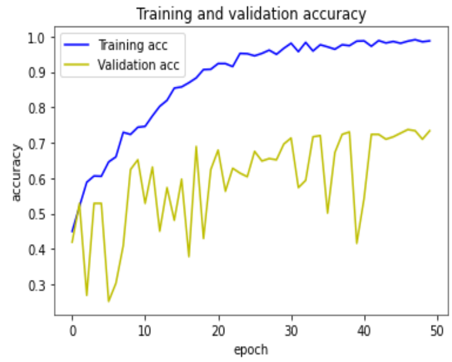


Fig. 5 Model Loss of R-CNN model

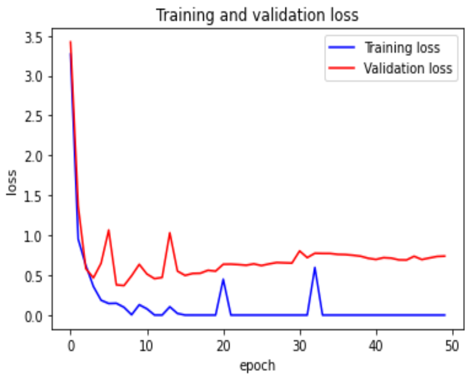


Fig. 6 Model Accuracy of CNN model

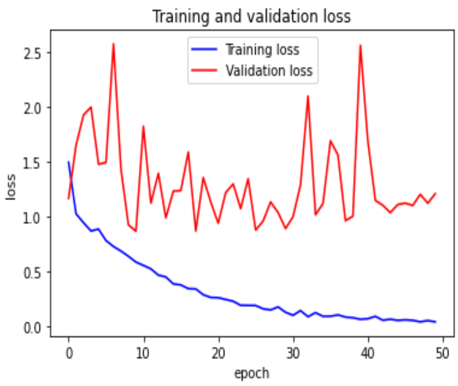


Table I. Performance metrics I (overall)

Model	Classification Performance (%)		
	Accuracy	**Sensitivity**	**Specificity**
CNN	73	72	72
R-CNN	91	90	89

TABLE II. PERFORMANCE METRICS II (CLASS WISE)

Model	Classification Performance (%)			
	Class	**Precision**	**Recall**	**F1 Score**
CNN	Type 1	76	45	56
	Type 2	72	87	79
	Type 3	75	65	70
R-CNN	Type 1	93	86	89
	Type 2	92	93	92
	Type 3	90	92	91

V. CONCLUSION

In this paper, we presented the Region based convolutional neural network for cervix type classification based on transformation zone, so that appropriate treatment can be provided to cervical cancer patients. Simulation results shows that Region based convolutional neural network model provides better performance compared to basic convolutional neural network model with an accuracy of 91%. In future work we intend to reinforce the segmentation approaches in order to further improve the obtained rates.

REFERENCES

[1] I. A. for R. on Cancer, "Latest global cancer data: Cancer burden rises to 18.1 million new cases and 9.6 million cancer deaths in 2018," *Press Release*, no. September, pp. 13–15, 2018.
[2] J. W. Sellors and R. Sankaranarayanan, "Colposcopy and Treatment of Cervical Intraepithelial Neoplasia. A Beginner's Manual," *IARC Press*, 2013.
[3] Z. Most and U. Kingdom, "Colposcopic terminology : the 2011 IFCPC nomenclature," pp. 51–57, 2011.
[4] Kaggle, Intel & MobileODT Cervical Cancer Screening (2017). https://www.kaggle.com/c/intel-mobileodt-cervical-cancer-screening/. Accessed 12 May 2019
[5] A. Quteishat, M. Al-Batah, A. Al-Mofleh, and S. H. Alnabelsi, "Cervical cancer diagnostic system using adaptive fuzzy moving k-means algorithm and fuzzy min-max neural network," *J. Theor. Appl. Inf. Technol.*, vol. 57, no. 1, pp. 48–53, 2013.
[6] P. Anguraj and T. Krishnan, "Design and implementation of modified BCD digit multiplier for digit-by-digit decimal multiplier," Analog Integr. Circuits Signal Process., pp. 1–12, 2021.
[7] T. Krishnan, S. Saravanan, A. S. Pillai, and P. Anguraj, "Design of high-speed RCA based 2-D bypassing multiplier for fir filter," Mater. Today Proc., Jul. 2020, doi: 10.1016/j.matpr.2020.05.803.
[8] T. Krishnan, S. Saravanan, P. Anguraj, and A. S. Pillai, "Design and implementation of area efficient EAIC modulo adder," Mater. Today Proc., vol. 33, pp. 3751–3756, 2020.
[9] N. Kaur and N. Panigrahi, "Automated Cervical Cancer Screening Using Transfer Learning," pp. 2110–2119.
[10] N Thendral, D Lakshmi, "Performance Comparison of SVM Classifier based on Kernel Functions in Colposcopic image Segmentation for Cervical Cancer", *Springer Series: Lecture Notes in Computational Vision and Biomechanics*, 2019, ISBN No: 978-3-030-00664-8, Vol 30, pp.1835-1844.
[11] J. Payette, J. Rachleff, and C. de Graaf, "Intel and MobileODT Cervical Cancer Screening Kaggle Competition: cervix type classification using Deep Learning and image classification," *Stanford Univ.*, no. February, 2017.
[12] X. Q. Zhang and S. G. Zhao, "Cervical image classification based on image segmentation preprocessing and a CapsNet network model," *Int. J. Imaging Syst. Technol.*, vol. 29, no. 1, pp. 19–28, 2019, doi: 10.1002/ima.22291.