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ANALYSIS AND DETECTION OF CERVIX CANCER USING DEEP LEARNING TECHNIQUES: A REVIEW

P. PHEBE, R. PARVATHI*

School of Computer Science and Engineering, Vellore Institute of Technology - Chennai, Vandalur -Kelambakkam road, Chennai, Tamil Nadu, 600127, India
*Corresponding Author: parvathi.r@vit.ac.in

Abstract

Early detection and classification of cervical cancer helps to promote consistent clinical management of patients. Different forms of computing approaches have been employed to detect the most cervical cancer. This survey examines the recent advancements in the domains of research from January 2018 and December 2021. Several literature reviews identify the investigated factors that influence women's participation in screening programs, the psychological response to the consequences of abnormal cervical smear, and the experience of colposcopy. Reasons for non-participation include administrative errors, lack of screening for women, inconvenient consultation hours, lack of awareness of the indications and benefits of testing, awareness of no risk of developing cervical cancer, and embarrassment. Cancer can cause discomfort or dread of being discovered. The reviewed study investigates distinct pre-trained convolutional neural networks architectures for diagnosing cervical cancer and pre-cancerous lesions, including Inception v3, You Only Look Once v4, and Colposcopy Ensemble Network. By giving more information, increasing communication, and addressing women's health beliefs, the quality of cervical screening programmers can be enhanced. This may increase your involvement in the service and your pleasure with it. This research looked into further exploration of deep learning approaches for segmenting and classifying cervical cancer.

Keywords: Cervical cancer, Deep convolutional neural network, Pre-trained CNN models.

1. Introduction

Cervical cancer is a type of cancer that develops within the cervix's cells. The vaginal human papillomavirus interacts with the bottom region of the uterus (HPV). To begin with, cervical cancer is localized in the cervix and does not spread to adjacent tissues or other organs. The tumor is so little that it can be seen with microscopic or colposcopy. In contrast, if the tumor is bigger, but still localized in the cervix, cervical cancer creates in the cervix, and it pretends to be absent from the uterus. Cervical cancer happens when ordinary cells within the cervix alter into cancer cells. This regularly takes a long time to happen, but it can too happen in a brief period. In 2020 [1], the worldwide mortality insights expanded over 340,000 ladies and these are likely to proceed to develop, especially in underprivileged and defenseless communities. Treatment of an injury, which could be a pre-cancerous zone, depends on the following after components: (i) the measure of the injury and the type of changes that have happened within the cells. (ii) The craving to have children in the future. (iii) Age (iv) common well-being (v) inclinations of the patient and the specialist. It happens most frequently in ladies over the age of 40. The frequency of cervical cancer in Nigeria is 250/1000000 per year [2]. The estimation of worldwide cervical cancer predominance is 11.7% among cancer illnesses where over 855 prevails in creating countries. Several modalities utilized for imaging purposes, including CT scans, MRI scans, nuclear medicine imaging, ultrasound, and X-rays are depicted in Fig. 1.

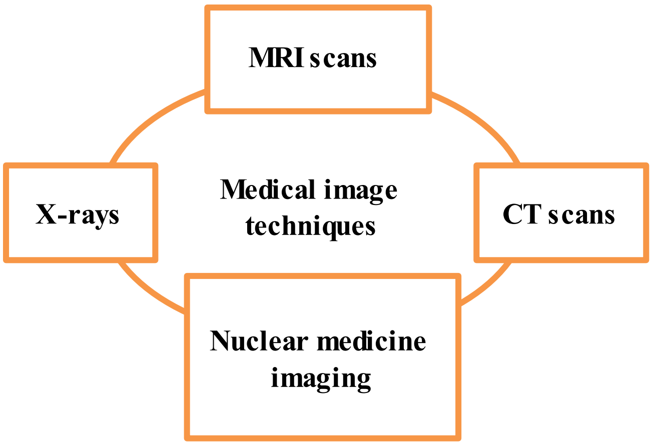

Fig. 1. Medical imaging techniques.

2. Activation Function

ReLU is utilized for quick preparation of the picture set by mapping negative esteem to zero and keeping up positive values which are referred to as the activation function. The functions that decide a certain yield or enactment for a particular collection of input data depending on its weight are known as activation functions. This technique is designed to address the sigmoid enactment function problem.

$$F'(x) = \begin{cases} 0 \; if \; x \leq 0 \\ x \; if \; x > 0 \end{cases} \tag{1}$$

To improve and alter the traditional rectified linear unit and unravel more complex and non-linear functions, authors in [3] presented another enactment work namely Leaky ReLU. The main goal of Leaky- rectified linear unit was to shed light on the topic of ReLU. As a result, this method proposes a tiny data leak within the yield-zero regions. As a result, the angle will be small but not zero, and neurons will not become dormant as a result of the weights being balanced. According to this study, in the situation of negative input, the comparative yield will increase.

$$F(x) = \begin{cases} \propto x \ if \ x \leq 0 \\ x \ if \ x > 0 \end{cases} \tag{2}$$

This has the gradient of,

$$F'(x) = \begin{cases} \propto if \ x \ \leq 0 \\ 1 \ if \ x \ > 0 \end{cases} \tag{3}$$

In case α = 0; x is an input variable; F gets to be Rectified linear unit.

If α > 0; F gets to be Leaky-Rectified linear unit.

If α may be a learnable parameter, F becomes parametric rectified linear unit.

The experimental findings of the existing classification approach employed by researchers in related works are compared in Table 1. The accuracy, precision, and F1 score metrics are used to assess a classifier's performance. The proportion of total methods is positive, and the proportion of total excepted negatives is negative which is called accuracy.

Table 1. Experimental results from associated work.

Citations	Classification Methods	Accuracy %
[4]	DenseNet-201	90
[5]	CYENET	85.8
[6]	HDFF	99.7
[7]	VGG-19	91.6
[8]	ResNet-50	88.4

3. Pre-trained CNN models

The pre-trained picture classification helps to extract effective and instructive highlights from normal pictures and use them as a beginning point to memorize a modern task. Employing a pre-trained model, that is organized with extract learning is regularly much speedier and less demanding than preparing to arrange from scratch. The cervigram picture is the input to the cervix classification problem, and the likelihood of the picture having a place to categorize I/II/III is the output [9]. The convolution last layer could be a fully associated layer that employs the softmax activation function.

3.1. Inception v3

For the picture classification model, Inception v3 could be used widely. On the picture dataset, it achieves a precision of 78.1 percent. It is based on initial publication titled "Rethinking the inception engineering for computer vision."

Inception v3 model [10] proved that it occurs with better accuracy than the VGG 19 and ResNet 50 model. On more than a million photos from the Image Net database, you'll be able to stack a pre-trained version of the trained network. The network has discovered that affluent people have representations for a wide range of imagery.

3.2. ResNet 50

ResNet 50 is based on residual learning, and it makes training of deeper network simpler. These models are fine-tuned on the cervix dataset. ResNet 50 is a convolutional neural network that has 50 deep layers [11]. On more than a million photos from the Image Net database, you'll be able to stack a pre-trained version of the trained network. ResNet snatched first place in the Image Net [12] challenge classification, with an error rate precision of 3.75 percent.

3.3. YOLO v4

You Only Look Once v4 are the classification method for identifying abnormal or normal images of cervical cancer. Cell discovery by YOLOv4 [13] was able to identify all typical algorithms that contributed to the change in the system precision. You only look once cell detection methods are used to detect the typical cell cluster (ASC-US) cells over ASC-U without any watched wrong negatives. At that time, the identified cell pictures were evaluated. The accuracy metrics is mentioned in Fig. 2.

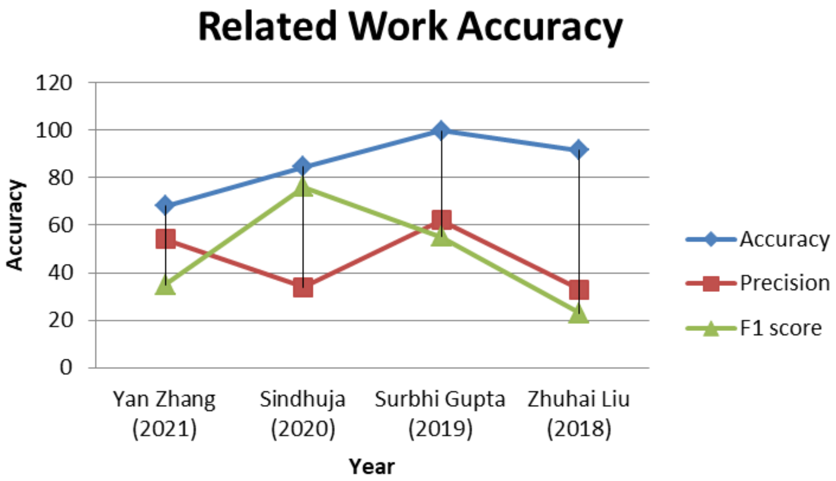

Fig. 2. Comparison of various researchers' findings based on their accuracy.

3.4. CYENET

The CYENET was created to automatically classify cervical tumours from colposcopy pictures. The suggested CYENET appears to have high sensitivity, specificity, and kappa scores of 92.4 percent, 96.2 percent, and 88 percent, respectively, according to the test results [14]. Convolutional layers, 12 activation layers, five max pooling layers, and four cross channel normalisation layers are included in the CYENET model. The overall dataset and algorithms of related works are mentioned in Table 2.

Table 2. Overview of literature review.

Citation	Dataset	Algorithm & Model	Result
15]	Thin prep cytologic test (TCT) image.	Deep learning models; 1.CNN 2.CNN+SPP 3.CNN+Inception	Accuracy 86.3% Sensitivity 84.1% Specificity 89.8%
[16]	Colposcopy image.	Deep belief network	Accuracy 84%
[17]	SIPKaMed Whole slide image.	CNN: ResNet- 34 ResNet- 101 Efficient Net B3	Accuracy 98.91% Precision 98.92% Recall 98.91% Specificity 99.10% F1-Score 99.01%
[18]	Pap Smear images.	Hot spot detection method. Pigeon-Inspired optimization method.	Accuracy 99.65%
[19]	Cytology images.	DeepCyto	Accuracy 97%
[20]	Herlev dataset.	Convolution neural network method: Auto encoder	Accuracy 99.5%
[21]	Pathological images.	Deep Convolution Neural Network model: GoogeNet VGG	Accuracy 93.3%
[22]	Cervix images.	Inception V3 ResNet50 VGG19	Accuracy 96.1%
[23]	Colposcopy images.	Cervical lesion segmentation model: EfficientNet-B3	Accuracy 93.04%
[24]	Mobile ODT images.	Retina Net VGG ResNet	Accuracy 92.43%

4. Conclusion

This research paper reviews the number of recently published articles for automatic detection and classification of cervical cancer from the various dataset. This work will assist researchers in understanding what is going on in this sector and will provide a solid foundation for building and developing new algorithms, as well as improving existing ones. In this study, a scientific deep learning model was developed for diagnosing various cervical cancer scenarios. Cervical cell and the various risk factors that contribute to its development have been studied utilizing computational and numerical methodologies in medicine. Furthermore, the multi-class classification studies will be conducted on both datasets (Herlev and SIPKaMed) to improve the further component extraction matters from malignant growth images. The researchers hope to incorporate image-specific saliency maps into learning in a more systematic way and enhance by adding the input data to improve segmentation accuracy. They can implement an automated system for the detection and classification in mobile phones; websites and any HTTP network so that images can be sliced into layers for attending subgroup analysis with sample tissues from the women, a significant number of cases are required. More filters in convolutional layers could increase the network's performance by highlighting the act white region's margin and texture within that region.

Nomenclatures

F	Rectified linear unit
x	Input variable
α	Learning parameter

Abbreviations

ACSUS	Atypical cell cluster
CNN	Convolutional neural network
CYENET	Colposcopy ensemble network
HDFF	Hybrid deep feature fusion techniques
ReLU	Rectified linear units
ResNet	Residual network
YOLO	You only look once

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