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Feature Extraction and Classification of Overlapping Cervical Cancer Cells using Convolutional Neural Networks

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***Abstract*—Cervical Cancer is the fourth most common cause of cancer and death in women [1]. India has one of the largest numbers of cases of cervical cancer and efforts are made to reduce the number of fatalities by improving the techniques of detection. The steps that are followed includes obtaining the microscopic images by Liquid Based Cytology(LBC) method, followed by the classification of the visual input. For this method of classification convolutional neural network is used which is a very powerful technology for the classification of the visual input arising from the detection process. The convolutional neural network used here is the Inception v3. The end-result is the accurate classification of overlapping as well as non-overlapping cervical cancer cells.**

***Index Terms*— Convolutional Neural Networks, Cervical Cancer, InceptionV3, HPV virus, LBC.**

I. INTRODUCTION

Cervical cancer is the fourth most common cause of cancer and cancer death in women, an estimated 12,820 women in the USA will be diagnosed with cervical cancer and about 4210 death will occur this year. There is a higher incidence of cervical cancer in developing countries especially India, as per estimates 70% of cervical cancer occurs in developing countries and in a low-income country this is the most common cause of cancer death. Interestingly India accounts for roughly one-fourth of all the cases of cervical cancer. However in developed countries due to the easily accessible and affordable clinical screening available, has caused a dramatic reduction in the rates of cervical cancer.

Women between the ages 40 to 55 are the most affected by this cancer. In recent times there has been a wide variation in the number of cervical cancer cases across the globe. Some of the risk factors include smoking, unprotected sex or having HIV infection, prolonged use of birth control pills [2]. In developed countries, there is a decrease in the number of death related to cervical cancer. This is primarily due to early detection of cancer by means of regular screening.

So as to reduce the fatalities by regular screening, National Cancer Control Program (NCCP) formulated and

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funded by the Ministry of Health, Government of India has stressed upon the implementation of community-based cervical screening program at least in select districts of each state. This organization has made provision for funds to be given to all states to implement the cancer control program that includes cervical cancer screening activities.

Cervical cancer is caused when an abnormal cell in the cervix multiplies at a faster rate and grows out of control, this abnormal change causes the cervical cells to change into a precancerous state which is referred to as Cervical Intraepithelial Neoplasia (CIN). Based upon the degree or intensity of the cellular degradation it's classified as low-grade Cervical Intraepithelial Neoplasia and high-grade Cervical Intraepithelial Neoplasia. Cervical cancer is caused by a virus called as Human Papilloma Virus or commonly known as HPV. For the early detection of the HPV virus, there are few ways to detect it. The most populars ones for early detection are

(i) Pap test or also called as Pap smear - Here the test looks for the precancerous cell changes in the cervix.

(ii) HPV test - Tests for the presence of HPV virus which changes the cell structure changes .

One notable method of screening is the Liquid Based Cytology method (LBC)[3]. In this method, cervical samples are prepared for the purpose of examination and diagnosis in a specialized laboratory. This method has a better detection rate, hence the diagnosis is more accurate. For reference, this method is more accurate than the pap smear test hence the detection rate is higher with this method than that of pap smear test. However, the drawback of all the methodology is that despite obtaining the samples for the purpose of testing, there is always an element of human error and hence this will lead to erroneous results.

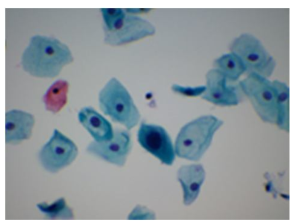

Figure 1. Example of Non-Cancerous Image

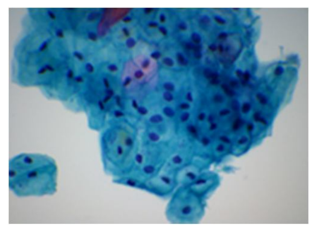

Figure 2. Example of Cancerous Image

This paper presents an efficient and accurate method for the diagnosis of cervical cancer using Convolutional Neural Networks (CNN). A CNN is a powerful tool that is used to classify visual inputs into different classes[4]. The reason CNN is widely successful in the task of classification is because the network is modeled on animal visual perception and therefore is well equipped to perform such tasks [5]. Also structurally, the CNN contains multiple layers of receptive fields which have to process portions of input images and then the output is tiled so that the regions overlap, thereby creating a higher-resolution representation of the original image, this is repeated in all layers[6].

In comparison to other image classification algorithms,there is very less pre-processing in CNN. Hence the filters are learned instead of being hard-coded in traditional algorithms. Hence, in this network there is no need for a human to hand-engineer, which is a major advantage of CNN.In this regard, we are using the Inception V3 which is one of the best image classifier among CNN.The image below gives an understanding into the performance of the Inception V3 with respect to other CNN models.

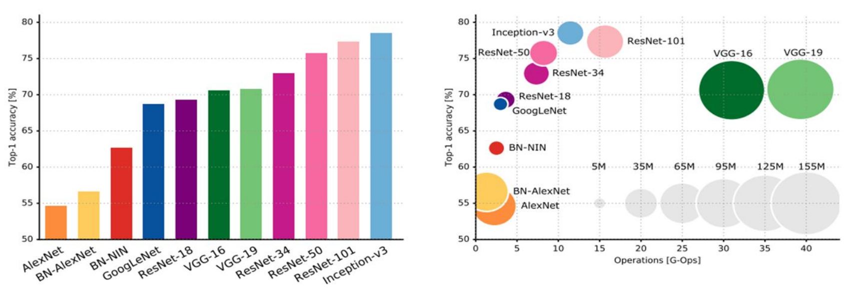

Figure 3..Comparison of Inception V3 with other CNN models

II. Data set

Data Set has been obtained from a pathologist and it includes about 460 LBC images in .jpg format.LBC screening method has a better detection rate, hence the diagnosis is more accurate.With a count of 197 cancerous and 263 non-cancerous images. Image dimensions- 2040x1528; Horizontal and vertical resolution 96 dpi; with a bit depth of 24 has approximately 10 to 30 cells per image.

III. Labeling the images

One of the visual clues to detect a cancerous slide is the nucleus to cytoplasm ratio. This ratio is very high for cancerous cells. Another thing to note in the images is the dense clustering of the cells which is rather common for cancerous cells.

For the purpose of training the neural network,two classes have been considered - cancerous and non-cancerous. The images are trained using supervised learning algorithm, wherein the images are labeled and the classifier learns the special features from the images fed to it.Thus,the network will be able to learn the important features for classification[7].

IV. Training the Network

The network is trained for 1500 steps with a cross entropy of 0.13201,which is the loss function in machine learning and optimization[8]. In machine learning, cross entropy is defined as the

The data is as given below.Increasing steps results in smaller cross entropy values, leading to more accurate results. Also, the network converges quite quickly, as indicated from the initial values.

V. Implementation using tensorflow

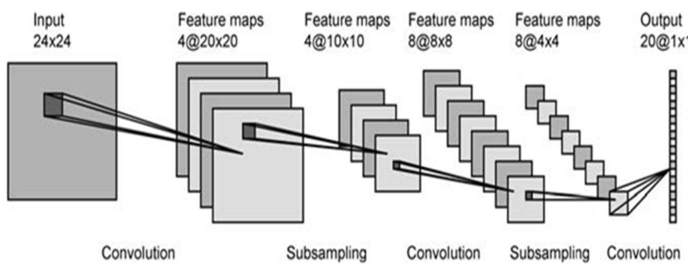

Figure 4. Working of convolutional network

In CNN, one of the best image classifiers is the inception-v3 [9]. This is the classifier that is used for the classification purpose[10]. This network has been seen in existence since 2014 and the quality of network architecture has significantly improved by utilizing deeper and wider networks. This has been successful for a wide variety of computer vision tasks such as object-detection, segmentation, human pose estimation, video classification, object tracking , and superresolution[11].

Computational cost in Inception is lower in comparison to other CNN's[12]. This has made it feasible to utilize Inception networks in big-data scenarios, where a huge amount of data needed to be processed at reasonable cost or scenarios where memory or computational capacity is inherently limited, for example in mobile vision settings[13]. It is certainly possible to mitigate parts of these issues by applying specialized solutions to target memory use, or by optimizing the execution of certain operations via computational tricks.These modification comes with added difficulties. Furthermore, these methods could be applied to optimize the Inception architecture as well, widening the efficiency gap again. Still, the complexity of the Inception architecture makes it more difficult to make changes to the network. If the architecture is scaled up naively, large parts of the computational gains can be immediately lost[14].

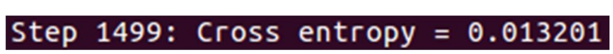

Figure 5. Final Cross Entropy value

V. Simulation Results

From the simulation, it is clear that the result of the classifier is very accurate and the data presented to the classifier for the purpose of testing were not the ones it was trained with and was able to classify it with good accuracy.By increasing the number of steps smaller cross-entropy have been achieved, which results in better outputs.

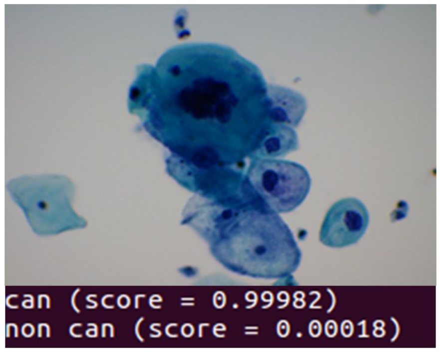

Fig. 6 & 7. Cancerous Image along with the results

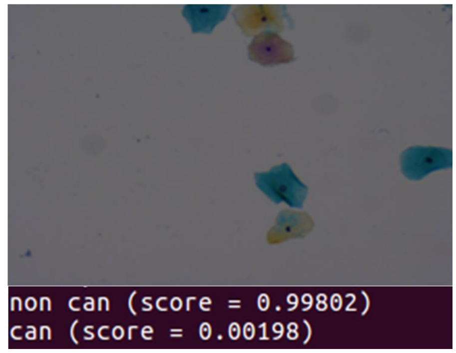

Fig. 8 & 9. Non-Cancerous Image along with the results

TABLE I. STEP SIZE VS CROSS ENTROPY

Steps	100	200	300	400	500	600	700	800	900	1000
Cross Entropy	0.097626	0.066049	0.0455	0.028207	0.0303	0.033341	0.0154	0.022108	0.019799	0.019996

VI. Conclusion

This paper has presented the implementation of a biomedical image classifier using inceptionV3 and the results have reached upto 100 percent accuracy .The CNN model used here is a powerful tool that has classified the images in two categories.The quality of image is quite important and the image that offers data should not be contradictory in nature, thereby causing the classifier to give errors. The CNN provides a very good accuracy and is robust in comparison with the other image techniques used.

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