Diagnosis of Carcinoma from Histopathology Images using DA-Deep Convnets Model

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***Abstract*—Cancer is a major origin of mortality around the globe, responsible for roughly high morbidity and mortality in 2020, or almost one per six deaths. Cervical, lung, and breast are the most common types of cancers. Cervical is the fourth highest common in women worldwide. Cervical would then kill approximately 4,280 women. Infections that cause, such as human papillomavirus (HPV) and hepatitis, account for approximately 30% of cases in low- and lower-middle-income countries. Many cancers are curable if detected as early as possible. In this proposed work, developed the DA-Deep convnets model (Data augmentation with a deep, Convolutional Neural Network) for the detection of cervical cancer from biopsy images. Deep Convolutional Neural Network presents one of the most applied DL approaches in medical imaging. Today, enhancements in image analysis and processing, particularly medical imaging, have become a major factor in the improvement of various systems in areas such as medical prognosis, treatment, and diagnosis. Based on our proposed model we achieved 99.2% accuracy in detecting the input image has cancer or not.**

Keywords*—Cancer; cervical cancer; convolutional neural network; deep learning

I. Introduction

The American Society's estimates for cervical in the US in 2022[16]: "There will be approximately 14,100 new cases of invasive cervical given a diagnosis." Oncology encompasses a wide range of diseases that can affect different parts of the body, collectively known as cancer. There are also terms like cancer and neoplasms in use. The term "metastasis" refers to the spread of cancer cells beyond the normal boundaries of the body. Diagnosing for a person looks to the doctor when they found some abnormal manifestation in the body. After that, the doctor checks that person's manifestation and medical history. Based on the symptoms the doctor will suggest a health check test. Some people may not have the manifestation too. They are able to detect only through medical checks like a biopsy, or CT scan. Sometimes doctors will find after the screening test only such as Pap test or mammography.

A. Types of Cervical Cancer

A lab microscope is used to classify cervical s and pre-cancers. Squamous cell carcinomas and adenocarcinomas are the most common types of cervical [18].

1) In most cases of cervical (up to 9 out of 10), squamous cells are present. They arise from ectocervical cells. The most common site of squamous cell carcinoma is the transformation zone.

2) Adenocarcinomas is one of the majority of cervical cancers, it is generated from the glandular cells Adens. Cervical adenocarcinoma evolves from endocervical mucus-producing gland cells.

3) Adenosquamous or mixed carcinomas are identified when both features are detected in the cervical.

B. Standard Screening Tests for Cervical

1) The HPV Test: By taking the sample piece of the DNA (Deoxyribonucleic Acid) from the cervix the doctor is able to identify, this procedure is referred to as the HPV (Human Papilloma Virus) test. HPV will not detect cancer. It will determine only the presence of HPV that cause cervical. When the person has HPV type 16 and 18 there is a possible cervical risk. In the test, doctor will collect the cell from the cervix and look at the changes caused by the HPV. Visual Inspection with Acetic Acid (VIA) is another method for detecting precancerous cervical lesions. A pathologist applies acetic acid (diluted vinegar) to the cervix to see if there are any changes in the cells. Women are given the results of the VIA test right away. In a Cone biopsy, the doctor will detach a cone-shaped piece of tissue from the cervix, called conization. The tissue includes the transformation zone where cervical pre-s and s are most likely to start also sometimes it will completely remove the early cancerous too. Few general concepts are explained in less technical terms to help you better understand how doctors decide if cancer is presently using the Shape and size of the cells, Nucleus shape, and size.

Based on the above-mentioned, the pathologist identifies cancer from the biopsy images using microscopy manually through the more number of slices in tissue after the progress. So, when they are diagnosed with the biopsy images, they may have an error as a manual error. So, the result may come from those having cancer who don't have it and vice versa. So, in the proposed work, the automatic identification of cancer through the deep convolutional neural network is suggested. For getting more accuracy in the proposed model, generate the input with data augmentation.

II. Related Work

A survey was made about cervical cancer by the American society as more new cases were found as well as more number of death due to cervical cancer. In most cases, cervical cancer

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is prevented using the HPV vaccination based on the screening test. When diagnose earlier as possible it will be managed effectively. If cancer is found at later stages with suitable/relevant treatment and palliative therapy then it is possible to control it.

S. N. Eldin et al. [1] proposed the diagnosis of the breast using the biopsy images using the best three models of deep learning techniques such as Resnet50 & 101, Densenet 169 model, without doing the preprocessing of the images and with preprocessing the input images. Also in this work, they tell about the various preprocessing techniques based on the performance of the models. D. Bardou et al. [2] work regarding the classification of breasts automatically using machine learning and deep learning approaches. Classification is based on the benign or malignant with subclasses. They used two approaches for the classification extracting the feature using two coding models using SVM in the machine learning model and the second approach using the Convolutional Neural Network model in deep learning techniques. In this work, they generated the images using data augmentation techniques to increase the accuracy of the result. E. CENGİL et al. [3] detect lung cancer using the 3D Convolutional Neural Network model with the implementation of TensorFlow. Here the identification of the cancer is based on the CT images; also here they classified lung cancer as benign stage and malignant stage. Here they used only the less number of a dataset for detection and classification. Y. Li et al. [4] proposed work for the identification of gastric cancer as well as its classification. Here they did the pre-processing technique as cropping because of the large size of images in the given dataset so that the deep learning model can learn and train properly using the given dataset. Here they classify lung cancer based on the patch-based classification and the slice-based classification. Van Eekelen L et al. [5] here worked for the segmentation of the major cell and the tissue types in the bone marrow trephine biopsy images. Along with the input they have biopsy images for the different wide range of persons. Based on the given input they detect and segment using VGG 16 model. They also get the result from the pathologist and compare that result with the automatic detection of cancer using the deep learning model and give the accuracy compared with the pathologist data.

Koh J et al. [6] here worked on the detection of breasts using CT–images using the deep learning model. In this proposed work they also analyze their result with the internal and the external dataset. X. Dong et al. [7] proposed lung cancer detection and segmentation using the CT images with the help of Hybridized Fully Convolutional Neural Network deep learning model with the help of mathematical calculation. Here they performed the data augmentation during the training process. Identify the size using the pyramid structure and the texture classifier used to detect the normal and abnormal cells from the given set of images. Here they use the method to reduce the false-positive results. 2D feature maps are included for better feature extraction. Singla C, et al. [8], Mammogram screening plays an important screening for the detection of breast cancer. It has a very poor-quality image so it is very difficult for them to identify cancer from the given input. So, to enhance the image for the training they did the image enhancement with the help of the filters. They use the filters such as High PSNR and low MSE values. R. Roslidar et al., [9] in this work, detect breast cancer using Thermography images. Based on the thermograms screening model, doctors are able to detect cancer by observing the temperature distribution in the breast. Here they detect and classify cancer using a deep learning model. Actually to identify breast cancer with large tissue and early detection, can go for the thermography screening technique. So based on the temperature distribution only it is able to find out. It is very difficult for the pathologist to find out manually. So, to overcome these problems they used automatic detection using the deep learning model. To achieve a better result, they use the image enhancement model as a pre-processing method such as mean subtraction, and local contrast normalization. They also did the resizing such as width and height modified images. For the segmentation part, they use the ROI segmentation. L. Wei et al., [10] in this proposed work, classify using the dermoscopy images with the help of a deep learning model. Detection of lightweight skin cancer based on the image pre-processing, training, and fusion of an image. To overcome the overfitting problem in training progress for given input they did the data augmentation method. In pre-processing steps, they construct the positive pair and also construct the negative pair. Here for the segmentation, they use the Mobile net-V1 architecture. They loaded the input images with preprocessing, and in the training process they took 50 epochs. This paper also showed, the with and without discriminator model process accuracy.

1) *S. Sharanyaa et al., [11, 12]* based on the deep learning model in this paper, they identify early gastric. It is identified using endoscopy and CT scans with lightweight techniques. Before training, the noise part images are removed as pre-processing and the feature extraction is done by the color threshold algorithm. Here they also said about the part of the images having a greater number of the red color band in the given images. They proposed the Deep color net model for the identification of cancer. Find the maximum correlation between the pixels from the images using a test vector. They also highlighted the more spread area using the higher match score. Some pre-processing is also done such as resizing and the RGB image to grayscale conversion. Feature extraction and feature mapping are also done here for pre-processing the data.

Based on the survey of the paper the early detection of cervical cancer is much needed in the world nowadays. Because if it is found early, it can avoid the most last stage of cancer and also reduce the death rate. Due to manual detection sometimes it may get errors. Also it takes more time to detect cancer. So to overcome these problems it’s better to get the automatic detection in the medical field with the use of a deep learning model as the convolutional neural network.

III. Materials and Methods

In this section, here discussed the data set pre-processing of the images for accurate results. Also, the method used for automatic detection of cervical cancer is Convolutional Neural Network algorithm.

A. Data Set

In the proposed work, the data was collected from the Kaggle dataset. The dataset contains both normal biopsy images as well as cancer biopsy images. In the deep learning model, it needs to train both the normal and the images then it can ably learn by the Convolutional process during the training process. This dataset is again divided for training, testing, and validation processes. It contains the dataset in png format as an image format. So Convolutional Neural Network can learn the feature from the images by feature extraction in the convolution process. The data was in the zipped file format after that it will unzip the file for the data pre-processing for further steps.

B. Data Pre-processing

1) Data augmentation: Data augmentation was used to create additional images in the proposed work, and the Google Colab platform's Image data generator was used to put this idea into action. It is possible to bring the image data generator into Collab by way of the Keras preprocessing. The image has been rotated by 40 degrees, out of a possible 360 degrees. Every flipped picture will find its permanent home in the 3D model. The image has become distorted on all sides. Width shift = 0.2, Horizontal shift = true, Fill mode = nearest allows you to make an object in another image appear narrower or larger than it did in the original. The image has been flipped both horizontally and vertically. When an image is flipped, the pixels are rearranged, but the image's original qualities remain unchanged. Some photographs' vertical inversion is meaningless, but it has uses in cosmology and photography studies of microscopic objects. This is shown in Fig.1 along with the corresponding collab python code. Given algorithm 1 explains about the augmentation process.

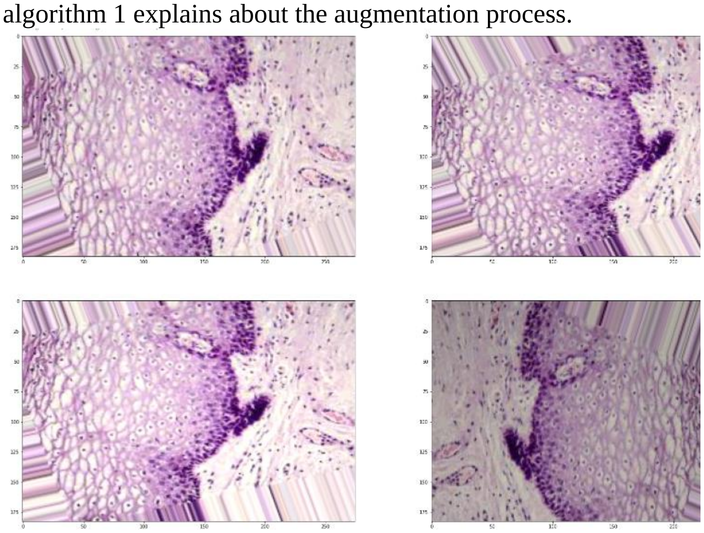


Fig. 1. Input Images with Data Augmentation.

Algorithm 1 Data Augmentation

Input: Normal and Cancer Images

Output: Augmented Images

for i to n images in dataset do

R[i]=>Rotate range from 0 to 30

R[i]=>Zoom range from 0 to 0.2

R[i]=>width shift range as 0.2

R[i]=>Height shift range as 0.2

End for

2) Image training and validation: The dataset is split 80:20 so that the model can be trained and validated on separate data sets, avoiding potentially biased data. All of the photos in the folders that have been designated to correspond with the designated class names will have their titles applied to them automatically. DataLoader also brings in the train's annotated pictures and its data tracks. This separates our dataset into two classes: "normal," representing a biopsy from a healthy person, and "," representing a random sample of data.

C. Proposed Model Architecture

1) Neural network: The goal of deep learning algorithms is to produce results that are competitive with human judgments by repeatedly analyzing data by a predetermined logical framework. This is achieved by deep learning, which uses a network of interconnected neural processors to create a complex computational model.

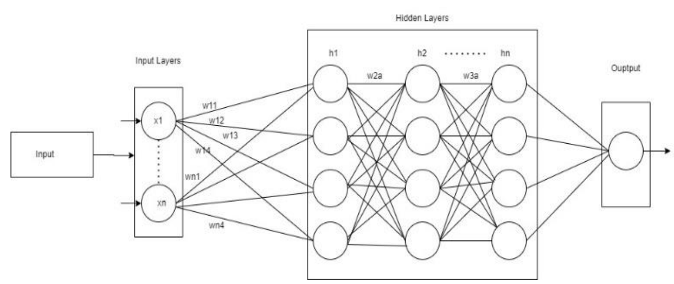


Fig. 2. Neural Network Architecture.

The Input layer in Fig. 2 above receives the data from the Output layer and does nothing with it other than pass it on. Weight, activation function, a deep network, and dense layers all work together in the hidden layer to process the input. Also it shows the connections between neurons and their associated weights (w) and hidden layers (h). What do weights mean? The weight assigned to a neuron indicates how strongly it is connected to other neurons in the network. Every neuron's output is computed using this method. Only the first input (with weights) is included in the Eq. (1) below.

$$Output = F\{[x1 * w11) + (x1 * w12) + (x1 * w13)] + [(xn * wn1) + (xn * wn2) + (xn * wn3) + (xn * wn4)]\} \quad (1)$$

The last hidden layer is then used to produce the output in the output layer. The four neurons in Fig. 2 will be used to generate the desired result. Each neuron in the network will have four weights used in the calculation.

2) Convolutional neural network

a) Convolutional layer: The convolutional layer is the first layer of a Convolutional Neural Network. Filters occupy a small portion of the input image's height and width but extend throughout its depth. It's been programmed to identify a specific class of features in the images, it's being shown. The filter or kernel is iterated through every possible location on the input matrix as part of the convolution layer. If the input image is I by I pixels and the filter is f by f, then the dimensions of the convolved output can be determined using below Eq. (2),

$$Dimension\ of\ the\ convolved\ ouput = [size\ of\ the\ input\ image - filter\ size + 1] * of[\ size\ of\ the\ input\ image - filter\ size + 1\ ] \quad (2)$$

The Eq. (3) for determining padding is as follows:

$$Output\ size = [i + 2p - f + 1] * [i + 2p - f + 1] \quad (3)$$

The input image's padded size is determined by the Eq. (4) provided,

$$Size\ of\ padded\ input\ image = (i + 2p) * (\ i + 2p) \quad (4)$$

Convolutional layer output can be obtained by performing the below Eq. (5),

$$Output\ for\ convolutional\ Layer = \frac{i - f + 2p}{s} + 1 \quad (5)$$

i represents the input image dimension i x i, f represents the filter size f, p represents the padding value, s represents stride value. After the convolutional layer, the output size is calculated to be 3x3, which is the result of the operations of padding, stride, and convolution.

The Eq.(6) used to determine how many pooling layers should be used.

$$Dimension\ of\ pooling\ Layer = \frac{input - filter}{stride} + 1 \quad (6)$$

Consider input as 4 x 4, Filter value as 2, Stride value as 2. Finally it calculates the input, weight, and bias value to predict the output using Eq. (7),

$$Ouput = ReLu[(i1 * w1) + (i2 * w2) + (in * wn) + Bias \quad (7)$$

i-represent the input layer, w-represent the weight, b-represent the bias value

ReLu is the activation function.

b) Dropout: As a workaround, a dropout layer is implemented. In order to reduce the training time and overall size of the model, this layer prunes the neural network of some of its neurons. The neural network has a dropout threshold of 0.3, at which point 30% of the nodes are removed at random.

c) Assertion of Activation: The model's final and most crucial parameter, the activation function is essential to any convolutional neural network. It merely chooses which bits of data should be sent forward and which ones should be left floating around indefinitely. Based on this, let's use Adam as an optimizer with a learning rate of 0.001. Consequently, our model's process is depicted in Fig. 3. It is based on all of the aforementioned layers, and it processes the operations and gives the output by training the images through all of the layers.

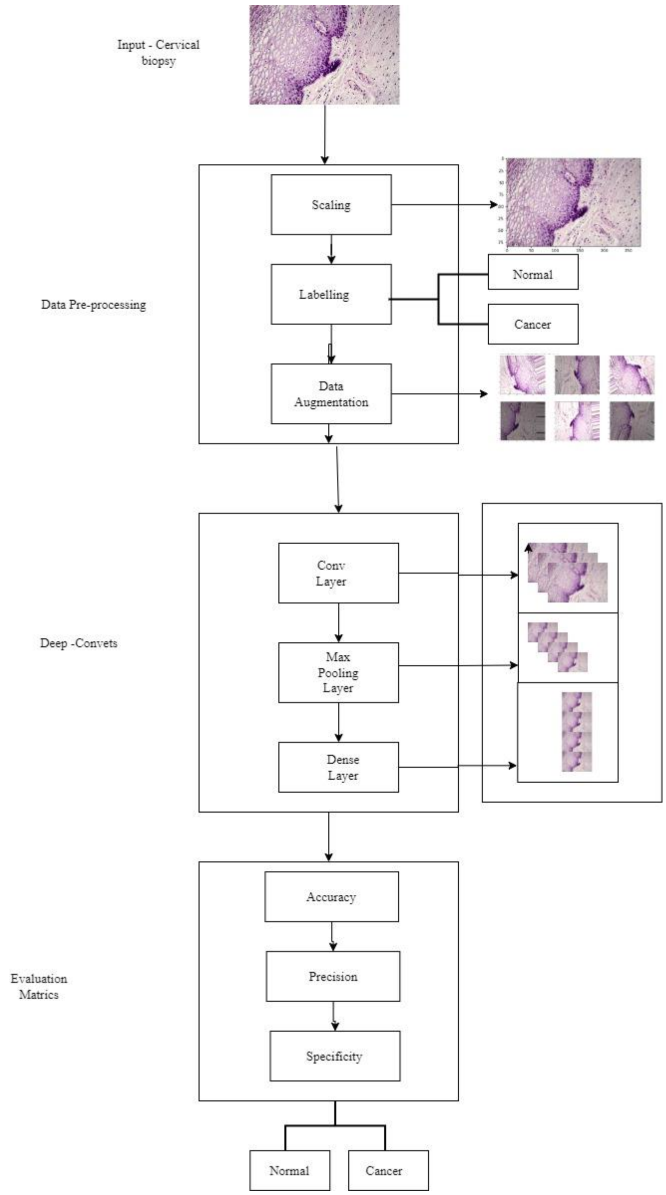
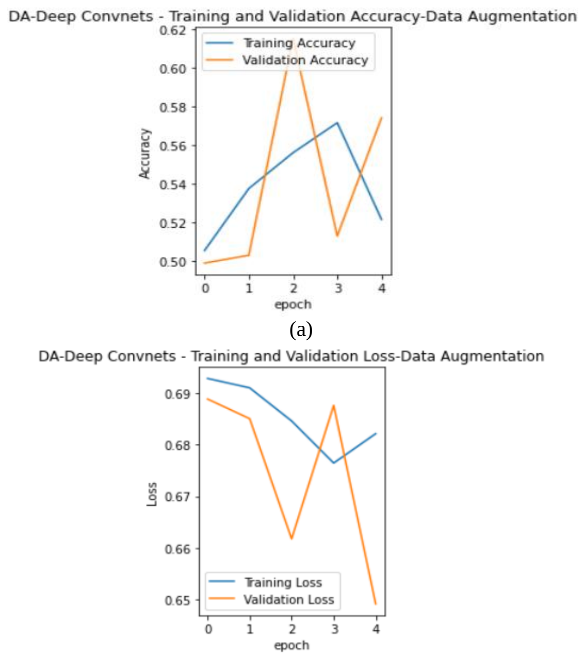


Fig. 3. Block Diagram of the Proposed DA-Deep Convents Architecture.

IV. Result and Discussion

Using the Kaggle dataset, the proposed DA-Convent model was implemented in Google Colab. We also compared unaltered images to those that had data superimposed on them. Data augmentation for the input images, while it takes more time, will result in higher precision than the raw input data.

Fig. 4(a) and Fig. 4(b) show the training and validation of accuracy and loss value. Here for data augmentation, consider a number of the epochs as four to validate the accuracy and the loss function for the given set of images.



(a)

(b)

Fig. 4. (a) Traning and Validation Accuracy for Data Augmentation (b). Traning and Validation loss for Data Augmentation

A comparison of the results obtained with and without data augmentation, as well as an explanation of how the data is changing, will be provided as an output. Therapeutic identification methods include measures like precision, recall, f-score, and accuracy. A confusion matrix can also be used to assess the quality of the model. The Confusion Matrix displays how the classification component becomes confused while making predictions. The confusion matrix displays four categories: the expected classes from the original problem as columns, and the actual classes as rows. The following Eq. (8), (9) and (10) is used to determine the accuracy and loss value of the DA-Deep Convnets model.

True Positive: Normal cell, detect as Normal cell.

True Negative: Really cancer cell, detect as cancer cell.

False Positive: Normal cell, detect as cancer cell.

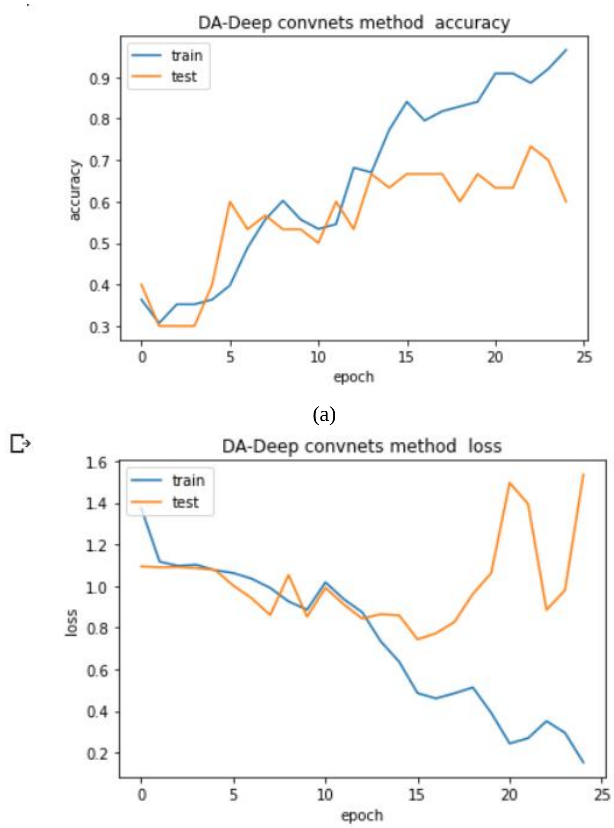
False Negative: Really cancer cell, detect as normal cell.

$$Accuracy = \frac{Number\ of\ classes\ correctly\ classified}{total\ number\ of\ classes\ taken} = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

$$Precision\ for\ Positive\ class = \frac{True\ Positive}{Number\ of\ cases\ predicted\ as\ positive} = \frac{TP}{TP+FP} \quad (9)$$

$$Precision\ for\ Negative\ class = \frac{True\ Negative}{Number\ of\ cases\ predicted\ as\ Negative} = \frac{TN}{TN+FN} \quad (10)$$

Based on the above equation, here calculated the performance for the given set of images and achieved more accuracy compared to the previous one. During the training process, here achieve more accuracy as well as reduce the loss function, as shown in Fig. 5(a) and Fig. 5(b).



(a)

(b)

Fig. 5. (a) Training and Testing Accuracy for DA-Deep Convnets Net Model with 25 Epoch, (b). Training and Testing Loss for DA-Deep Convnets Net Model with 25 Epochs.

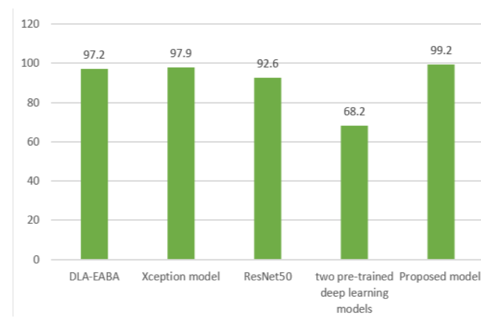


Fig. 6. Comparative Experiment Results of Proposed Architecture with different Models for Accuracy.

Fig. 6 shows the various comparative analysis with different models with the proposed model with reference [13, 14, 15, 17].

V. Conclusion and Future Work

In the proposed work, an intelligent health care design is developed for the detection of cervical cancer using the biopsy image. Currently, the incidence of cervical cancer is at an all-time high. One of the most important aspects of a patient's recovery is a timely diagnosis. One of the most popular visual recognition tasks is using Convolutional Neural Networks. Every day, CNN's position in the medical section grows stronger. In proposed DA-Deep Convnets model to create a more reliable model to assist dermatologists in accurately identifying cervical cancer. Accuracy in categorization and the top two was achieved through the use of data augmentation. With the help of data augmentation and the convolutional neural network, accuracy was achieved by 99.2%. In future work, we plan to do the classification and segmentation of cervical cancer for a more accurate process with more number of classifications.

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