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Custom Deep Learning Model for the Diagnosis of Cervical Carcinoma

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Abstract— Cancer is the second most common cause of death in the majority of the world due to late diagnosis. Most cancer cases are typically discovered at an advanced stage, which lowers the likelihood of recovery because proper therapy cannot be given at that time. In particular, for incurable cancers, which may result in a reduced life expectancy due to the rapid progression of the disease, the sooner cancer is identified, the more effective the therapy may be. Early detection also lessens the financial effects of cancer because treatment in the early stages is much cheaper than treatment in later stages.The method suggested is an end-to-end deep learning method in which the input photos are sent directly to the deep model, which makes the decision. The proposed Ensemble of deep learning modelIV3-DCNN to detect cancer in pap-test images. The model's precision, FScore, Specificity, Sensitivity, and accuracy of 99.4%, 99.23, 95.48, 97.9, and 99.2%. Last but not least, the suggested strategy would be very beneficial and successful, especially in low-income nations where referral mechanisms for patients with suspected cancer are frequently lacking, resulting in delayed and fragmented care.

Keywords- Cervical cancer,Papsmear,deep learning.

I. INTRODUCTION

[1].American Cancer Society estimates cervical cancer in 2022:Invasive cervical cancer will affect 14,100 people.Cervical cancer kills 4,280 women. Precancers are much more frequent than metastatic carcinoma. Pap testing detects pre-neoplastic changes in cervical epithelial cells.Traditional Pap testing uses cytology.Speculums are used to expose the cervix during Pap smear collection.The professional collects cervical cells with a spatula.Cells are put on a glass slide and sent to cytopathology labs for analysis.15,000 fields per image of cellular samples from a conventional exam must be manually analyzed by a cytopathologist under an optical microscope.Some countries do 100 smears per day.Two professionals should analyze the same smear to avoid false negatives.Due to physical and mental fatigue, the large volume of smears analyzed in one day causes errors in scrutiny and diagnostic interpretation.The procedure requires a specialist with a high level of technical knowledge, which reduces the number of people who can perform it and raises the cost of the exam.The Pap smear test has had limitations since the 1940s.At any stage of the exam, mistakes can happen that lead to false positives (when a lesion is found by mistake) or false negatives (when a lesion is missed).

The behaviour of the clinical patient is directly affect ed by these mistakes. If the doctor fails to notice the changes d uring the exam, the patient is left to suffer in silence as cervica l cancer develops. [2].A doctor incorrectly diagnoses a lesion c an cause unnecessary suffering for the patient by leading to ina ppropriate clinical action (like a biopsy or surgery). Recently made computer algorithms can now automatically analyse images of cells, making screening procedures more thorough and taking less time.
It is estimated that approximately 84% of all cases of cervical cancer and 88% of all deaths caused by cervical cancer occurre d in countries with fewer resources (i.e., those with an HDI of less than 80). In these countries, 1% of women were diagnosed with the disease and 1% died from it before the age of 75, ass uming that there were no other competing causes of death.cerv ical cancer's position in each country among other female cancers, overall, and among women aged 15-44.

[3]Certain strains of the human papillomavirus are responsible for virtually all cervical cancer (HPV) cases. The most reliable primary prevention against HPV-related diseases is HPV vaccination. When used by established protocols, the best ways to screen for cervical cancer are with the Pap test and the HPV test.[4]Rather than relying on an invasive pelvic exam, self-sampling is a more socially acceptable method of collecting

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samples. To increase screening participation and remove some of the obstacles connected with HPV testing, it is important to promote self-sampling and provide self-sampling kits. The link between the human papillomavirus (HPV) and cervical cancer has been brought to the public's attention through campaigns.

The primary contributions of this paper are listed above:

Cervical cytopathological images are obtained from the SIPaKMeD dataset used as the training data.

- In the pre-processing stage, labelling the data,scaling, and Normalization forthe training model.
- We implement 2 fined-tuned versions of (InceptionResNet_V3 and Deep Convolutional Neural Network) according.
- We tested single and ensemble on SIPaKMeDdatasets.

The remainder of the paper is organized as follows: Section 2 surveys deep learning-based methods proposed to cope with cervical cancer detection from Pap smear images. Section 3 presents a detailed description of the proposed approach, and discussesthe methodology. Section 4 provides the Experiment material and parameterization.Section 5 provides an analysis and discussion of the methodology. Finally, states concluding remarks.

II. RELATED WORK

In [5,18].The DL-based multiple fragmented for cervical cancer was proposed and tested to see if it could work. Theyshowed that a DL tool did as good a job of contouring as senior ROs doing it by hand and was better than what junior and intermediate ROs could do.[6]. The performance of the deep learning model of cervical cancer can be enhanced by having trained the affective region with much more pixel information than the peripheral part when the RGB channel superposition algorithm is applied to a cervical categorization image. Therefore, it is anticipated that professional staff will become more efficient and accurate at diagnosing cervical cancer in the future. Also, by giving different ways to measure how well act white works in deep learning, it is hoped that it will help develop a CAD system for diagnosing cervical cancer.In

[7] The advantage of the deep learning approach is that it can be used to analyze cervical LBC at the WSI level. Consequently, our model can infer whether the cervical LBC WSI is NILM or malignant. This enables using a deep-learning model such as ours as a tool to assist with cervical screening, which could be used to rank the cases in order of priority. In [8]COVID-19, pneumonia, lung cancer, and normal images are classified by this model. The gathered data consist of chest x-ray and computed tomography (CT) images. Based on the results of the experiments, the VGG-19+CNN significantly achieves each other's concepts.In [9,19]A Deep neural network (DNN) technique on the spectral characteristics of image pixels and a convolutional neural network (CNN) method with direct use of tomography (ct) images are provided.

This work was mostly about using deep convolutional neural networks to automatically classify cervical cells from Pap smear tests. The main goal was to get as many true-positive results as possible and as few false-negative results as possible. We attempted to employ modern convolutional neural networks, which were not used in previous works. We chose these architectures because they have a low cost of computation, which is good for methods like the ones proposed in this work.

III. MATERIALS AND METHODS

3.1 Description of the Dataset

The proposed model was evaluated using The SIPaKMeD pap smear dataset[12]. It consists of 4049 images. The cell images are divided into five categories based normal, abnormal and benign (i) Superficial-Intermediate, (ii) Parabasal, (iii) Koilocytes, (iv) Dyskeratotic, and (v) Metaplastic as given in Fig.1.

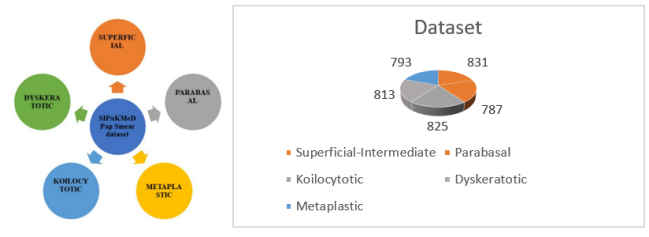

Fig.1.Dataset description

3.1.1Data Pre-processing:

Collecting and Cleaning Up Raw Data. For reliable classification results, preprocessing is crucial. It's a step in the data analysis process that comes before deciding how to file things. Preprocessing techniques are crucial for improving the model's classification accuracy on the "cancer data set." Class labelling, image scaling,random cropping, and sliding with the crop are some of the most common preprocessing techniques used in cervical cancer detection.Class labelling is used as a form of pre-processing step on a set of data dedicated to cancer.it is shown in shown fig.2.

3.1.2Preprocessing stage:

Enhancing the image quality is the first stage of pre-processing. The dataset images has2048x1536 pixels size we reduce the size of the image to 224 x 224 pixels.

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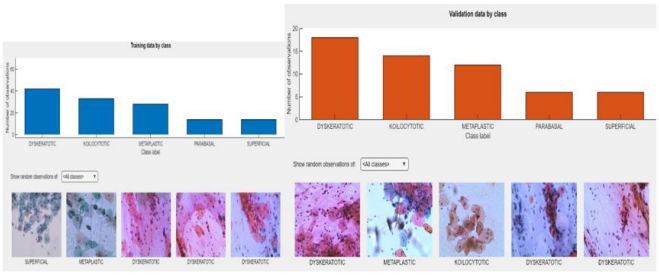

Fig.2.Dataset pre -processing

3.2Proposed Model

After preprocessing steps, the next section is to feed data into the proposed model (DCNN and InceptionV3). Thissection introduces the DCNN and Inception V3 model, including training parameters for cervical cancer detection and classification.

3.2.1Deep Convolutional Neural Network:

For simultaneous processing of the RGB channels, a Deep Convolutional Neural Network employs a three-dimensional neural network. To create a classifiers, deep convolutional neural networks take images for input. Instead of using matrix multiplication, the network uses the more specialized arithmetic operations of a convolution.Basic Architecture is given in Fig.3

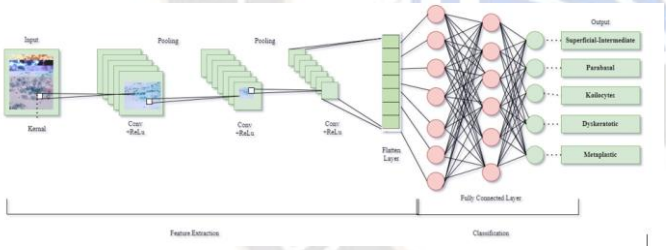

Fig.3. Highlight the basic architecture of the DCNN model

Deep Convolutional Neural Network:

The DCNN is the type of deep Learning Technique. This model performs the various layers of convolution operation to detect the images with cancer or not. The Layers are given below.

(a)Convolution Layer:

First Layer of DCNN model is used to extract the features from the given dataset images and for reducing the dimensions of the image the dropout layer, responsible. A network's effectiveness is affected by its depth. To calculate the convolution for a single pixel in the subsequent layer, we use the following equation (1),

$$X(c,d) = (I * F)(c,d) = \Sigma n \Sigma m I(n,m) F(c-n, d-m) \quad (1)$$

X-output for the next layer

I-input image

F-filter matrix

* - Convolution operation

Pseudocode for DCNN

DCNN process is represented as P

$$P = \{Da, Pr, DCNN, TT, CD\}$$

(a) Dataset(Da) Represented as,

$$Da = (im1\ , im2\ , im3\ , \dots\dots\ \ im\,n\ )$$

(b)Pre-processing is represents as Pr is given as,

$$Pr = (Pr1, Pr2)$$

Where Pr1 represents the reading the input,

Pr2 represents enhancing the images as splitting the images for validation, training and testing.

(C) Deep Convolutional Neural Network is represented as DCNN,

DCNN={C, MP, R, F, Si}

Step -1:*C represents the convolution operation,*

$$P^L = A^{L-1} * We^L$$

Step -2*:Max pooling is represented as MP,*

$$A^L_{ab} = max_{m=0,\dots n=0,\dots} A^{L-1}_{(a+m)(b+n)}$$

Step-3*:ReLU activation function is represented as R,*

$$f(r_a) = \max(0, r_a)$$

Step-4*:F represent the Fully connected Layer,*

$$P^L = We^L A^{L-1}$$

Step-5*:Si represents the sigmoid function,*

$$\mathrm{Si}(r_a) = \frac{1}{1+e^{-r_a}}$$

Where P^L – Pre activation output of Layer L,

A^L – Activation of layer L

* - convolution Operation

We^L - Weight (Learnable Parameters)

(d)Training and Testing represents the TT,

TT=(Tr, Te)

Tr represents the training images,Te represents the testing images. Both have different images for learning and validation.

(e) Carcinoma detection represent as CD,

CD=(0,1,2,3,4)

0 -Superficial-Intermediate,1-Parabasal,2-Koilocytes,3-Dyskeratotic and 4-Metaplastic.

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3.2.2Inception V3 Model

The Inception V3 model is a newer Google development of a valuable CNN that placed fifth overall in accuracy (0.928) at the ILSVRC-2015 competition. Initially, Inception approximated a sparse structure by grouping nodes from a non-uniform sparse data structure into a dense structure, allowing for greater precision without exceeding the available computational resources.Fig.4 shows how the inception V3 deep convolutional neural network is put together. A popular image recognition model is Inception v3. Average pooling, Convolutions, max pooling, fully connected layers and dropouts, are some of the asymmetric and symmetric building blocks that make up the model. The model makes extensive use of batch norm and applies it to activation inputs. Loss is calculated using Softmax. Factorizing Convolutions, initial work Convolutions with factorization are used to minimise the number of connections and learning parameters.This will speed things up and produce good results.

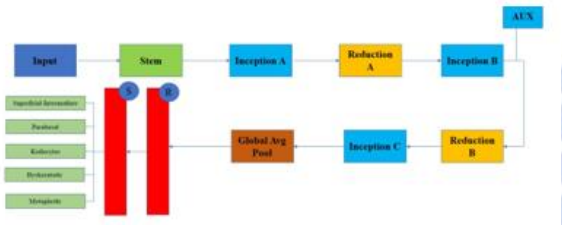

Fig.4 Basic architecture of the Inception V3 model

3.2.3Proposed ensemble model -Training and classification

The proposed models can be applied to the data after preprocessing and splitting, and the resulting features can be extracted it shown in Fig.5. Flattening the features extracted from each proposed model into a single layer allows for the final fully connected layer to be created, which is then used to categories images into their respective classes. In addition, each individual model that makes up the ensemble is trained separately to accomplish the target goal. The ensemble model's final output is a combination of the individual models' results. In addition, using an ensemble model can help you get the most out of your limited amount of training data by decreasing the variation in your predictions and generalization error. At last, the trained model is used to assess the efficiency of single and ensemble models on the testing set.

Pseudocode for Ensemble model

Input :SIPaKMeD dataset - pap smear image
Output: Types of cancer
1. Dataset preprocessing
Class labelling, image scaling, random cropping, and sliding
2. Feature extraction and classification stage
Producing the output1 using DCNN model.
Producing the output2 using InceptionV3 model.
3. Output1 & Output2 fusion stage
Fusing the output 1&2 to get the final decision

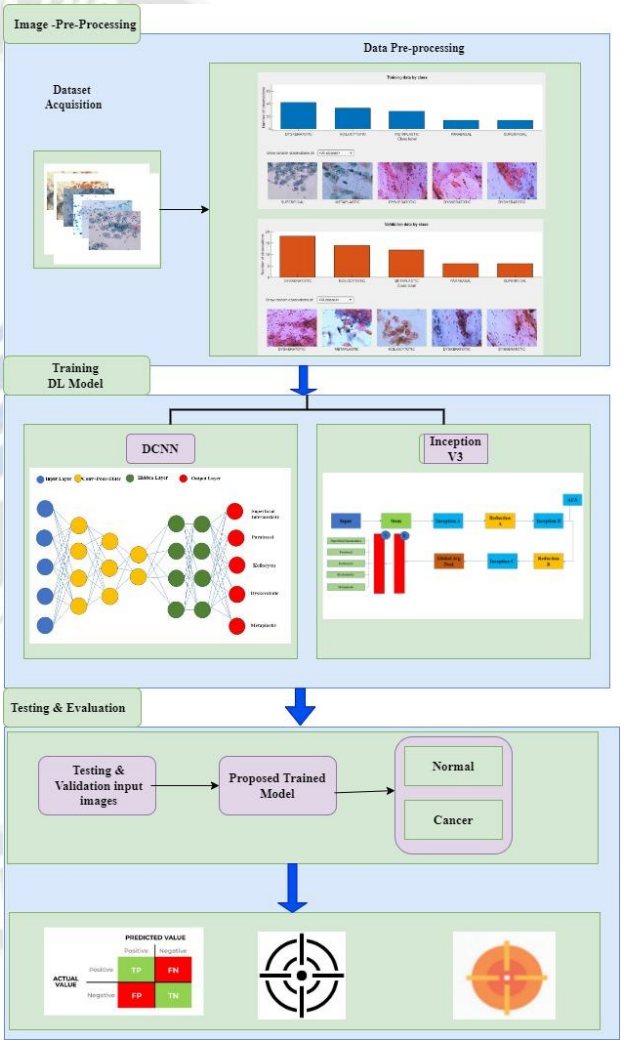

Fig.5 Proposed ensemble IV3-DCNN Model architecture

IV. EXPERIMENT MATERIAL AND PARAMETERIZATION

In order to forecast cervical cancer using single and ensemble models, the test configuration and effectiveness indicator used in this research are presented in this section. We point out that an ensemble model combines multiple single

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models, whereas a single model refers to a (DCNN or Inception v3) that was trained independently and predicted the outcome.

4.1 Quality assessment

Accuracy, sensitivity, specificity, and precision[26]is given in the below equations[2,3,4,5,6]. This research compared the performances of three models for cervical cancer image classification: the Deep Convolutional Neural Network (DCNN), Inception V3, and the proposed IV3-DCNN model. 0,1,2,3 and 4 are just some of the possible categories in any given model. As can be seen in Fig.10, the proposed model achieves the highest levels of precision, sensitivity, and specificity, while DCNN achieves the lowest. Parameterization of the experience is given in table 1.

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Positive + False\ Negative} \quad (2)$$

$$Precision = \frac{True\ Positive}{True\ positive + False\ Positive} \times 100 \quad (3$$

$$\text{Sensitivity} = \frac{True\ positive}{True\ positive + False\ Negative} \times 100 \quad (4)$$

$$\text{Specifcity} = \frac{True\ Negative}{True\ Negative + False\ Positive} \times 100 \quad (5)$$

$$\text{F1 score} = 2 \times \frac{sensitivity \times Precision}{sensitivity + Precision} \times 100 \quad (6)$$

Table 1Parameterization of the experience

Epoch :20

Model	**Total params**	**Trainable params**	**Non-trainable params**
Inception model	23,116,580	1,708,676	21,407,904
DCNN Model	2,624,002	2,624,002	0
IV3-DCNN Model	22,007,588	204,804	21,802,784

V. RESULTS AND DISCUSSION

This section presents and discusses the results obtained using the experimental setup that was covered in the preceding part for both single and ensemble models. The outcomes are broken down into two categories: single and ensemble.

5.1Results of single model

We begin by presenting the confusion matrix, accuracy, and loss curves (Fig 6 & Fig.7) that are generated by various deep transfer learning models while using the SIPaKMeD pap smear dataset, which contains Pap smear images that are class-imbalanced. Then, in order to determine whether or not cancer should be classified using the best method (Table 2), we evaluated by comparing the outcomes of all of the possible architectures based on the metrics established in equation (1).

From epoch 0 to epoch 20, we are able to see in Figure 2 that both the training accuracy and the testing accuracy for the DCNN model are rising till they reach a significance where they are equal to 95.18% and 94.01%, respectively. Likewise, for the Inception v3 model, the training accuracy and the testing accuracy values are 99% and 99%. An outstanding integration is seen for the loss curve of training and testing data for DCNN and Inception V3 model shown until the epoch 20 point in time. With regard to the confusion matrix, which is displayed accordingly.

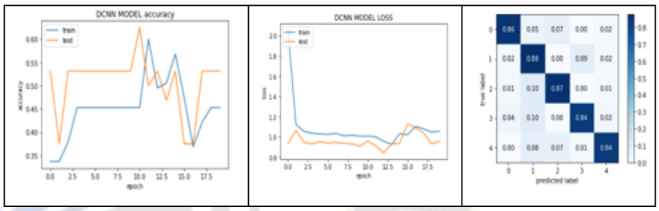

Fig.6 Accuracy,Loss and confusion Matrix for the DCNN model

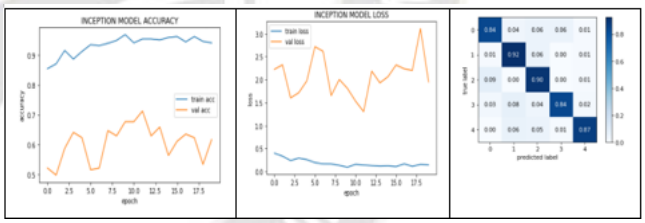

Fig.7.Accuracy,Loss and confusion Matrix for the Inception V3 model

5.2 Results of ensemble model

In the remaining part of this investigation, we will be concentrating on ensemble learning to determine whether or not there was an increase in performance indicators by applying equation 1. The purpose of utilizing ensemble learning is to demonstrate whether or not it can produce more accurate results than a single model can**.**Also the training and testing accuracy for the Ensemble IV3-DCNN model shown in fig.8. With regard to the confusion matrix, which is displayed accordingly.

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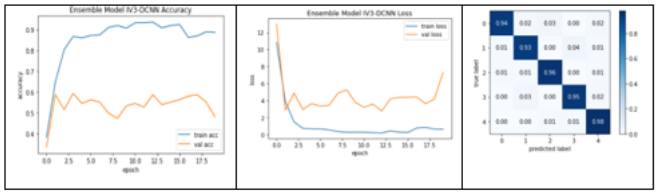

Fig.8 Accuracy,Loss and confusion Matrix for Ensemble IV3-DCNN model

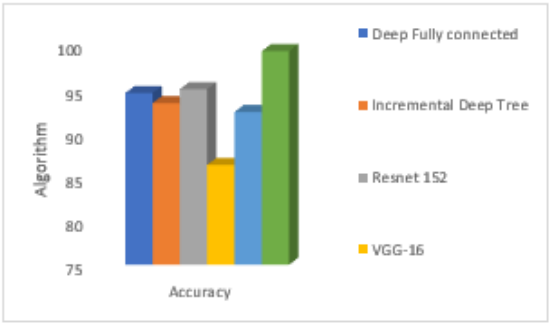

Fig.9.Comparative experiment results of proposed architecture with different models for accuracy.

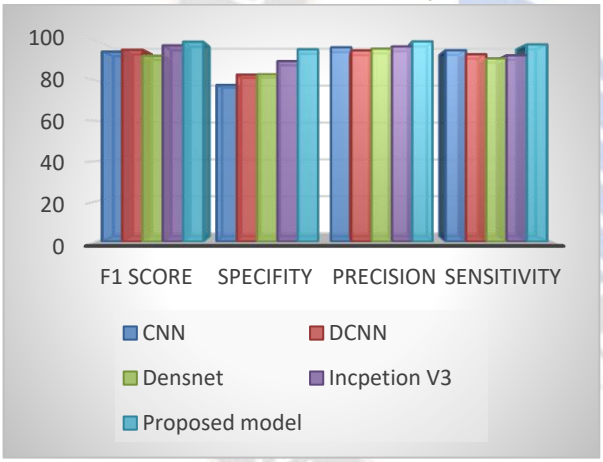

Fig.10 Comparison of evaluation metrics with different model

5.3 Discussion

Using fine-tuning, the proposed ensemble model achieves precision, F1Score, Specificity, Sensitivity, and accuracy of 99.4%, 99.23, 95.48, 97.9, and 99.2% .Fig.10. compares the precision, F1Score, Specificity and Sensitivity for the proposed model.The model outperforms individual deep models in precision, recall, F1Score, and accuracy. Unlike conventional CNN models, ensemble learning models that merge deep CNN acquire more useful features from training images. These ensemble models have done well in cancer image classification. Fig.9.shows the comparative accuracy for the proposed model to state-of-the-art ML/DL cancer classification algorithms[13-17].

VI. CONCLUSION

This study used Ensemble IV3-DCNN to classify cervical cancer detection. Numerous preprocessing techniques were used to prepare the model for optimal categorization. The testing used DCNN, InceptionV3, and ML/DL models. We classified cervical cancer samples using the SIPaKMeD pap smear dataset. The exploratory results showed that the proposed model achieves precision, FScore, Specificity, Sensitivity, and accuracy of 99.4%, 99.23, 95.48, 97.9, and 99.2%, reducing pathologist errors in inaccurate categorization and performing better than other models. The proposed ensemble IV3-DCNN model is computationally efficient and outperforms recent ML/DL algorithms to analyse model efficiency. The proposed model outperformed current methods for cervical cancer detection and classification. The ensemble IV3-DCNN model is a promising technique for classifying cervical cancer. This research can be expanded by adding one or more IV3-DCNN layers and tested on cancer multi-classification.

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