MAULANA AZAD
NATIONAL INSTITUTE OF TECHNOLOGY
BHOPAL, INDIA, 462003

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

Calcification of Cervix Using Deep Learning

Minor Project Report

Semester - 6

Submitted by:

Nikhil Kansliwal	191112024
Prabhat Kumar	191112025
Sachin Poonia	191112059

Under the Guidance of
Dr. Manasi Gyanchandani
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
Session: 2021

MAULANA AZAD
NATIONAL INSTITUTE OF TECHNOLOGY
BHOPALINDIA, 462003

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

CERTIFICATE

This is to certify that the project report carried out on "Classification of Cervix Using Deep Learning" by the 3rd year students:

Nikhil Kansliwal	191112024
Prabhat Kumar	191112025
Sachin Poonia	191112059

Have successfully completed their project in partial fulfilment of their Degree in Bachelor of Technology in Computer Science and Engineering.

_____

Dr. Manasi Gyanchandani
(Minor Project Mentor)

DECLARATION

We, hereby declare that the following report which is being presented in the Minor Project Documentation Entitled as “Classification of Cervix Using Deep Learning” is an authentic documentation of our own original work and to best of our knowledge. The following project and its report, in part or whole, has not been presented or submitted by us for any purpose in any other institute or organization. Any contribution made to the research by others, with whom we have worked at Maulana Azad National Institute of Technology, Bhopal or elsewhere, is explicitly acknowledged in the report.

Nikhil Kansliwal	191112024
Prabhat Kumar	191112025
Sachin Poonia	191112059

ACKNOWLEDGEMENT

With due respect, we express our deep sense of gratitude to our respected guide and coordinator Dr. Manasi Gyanchandani, for his valuable help and guidance. We are thankful for the encouragement that he has given us in completing this project successfully.

It is imperative for us to mention the fact that the report of minor project could not have been accomplished without the periodic suggestions and advice of our project guide Dr. Manasi Gyanchandani and project coordinators Prof. Sanyam Shukla and Prof. Namita Tiwari.

We are also grateful to our respected director Dr. N. S. Raghuwanshi for permitting us to utilize all the necessary facilities of the college.

We are also thankful to all the other faculty, staff members and laboratory attendants of our department for their kind cooperation and help. Last but certainly not the least; we would like to express our deep appreciation towards our family members and batch mates for providing the much-needed support and encouragement.

ABSTRACT

Cervical cancer is second most common female cancer globally and it is vital to detect cervical cancer with low cost at an early stage using automated screening method of high accuracy especially in areas with insufficient medical resources. Automatic detection of cervical intraepithelial neoplasia (CIN) can effectively prevent cervical cancer. Automatic and reliable cervical cancer detection methods can be devised through the deep learning methods on cervical images, using convolution neural network (CNN) for image analysis and CIN grading

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

Cervical cancer is second most female cancer worldwide ,with an estimated 604,000 new cases and 341,831 deaths in 2020.More than 80% cervical cancer deaths occur in less developed regions of the world .Therefore, it is necessary to detect cervical cancer at an early stages with low cost using automatic and effective screening methods ,especially in areas with insufficient medical resources .Cervical cancer screening is specially performed by detecting cervical intraepithelial neoplasia(CIN),also known as cervical dysplasia ,which is classified into three grades ,namely CIN1(mild), CIN2/CIN3(moderate), and CIN4(severe).

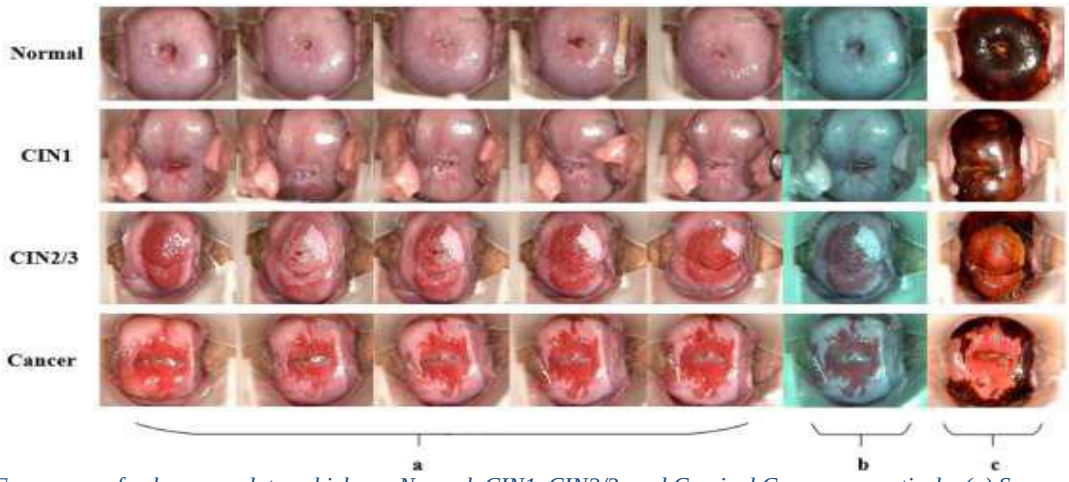

Figure 1 Four cases of colposcopy data, which are Normal, CIN1, CIN2/3, and Cervical Cancer respectively. (a) Sequential images photographed after applying acetic acid to the cervix uteri epithelium. (b) Image photographed after using green lens. (c) Image

In clinical practice, the primary target for cervical cancer screening is to determine the stages of CIN, such as normal, CIN1, CIN2, CIN3 and CIN4. Early-stage detection of this can be treated with normal medicines.

First, the surface of the cervix is wiped with a cotton cloth moistened with physiological saline to clean the cervical epithelium, and a regular network of branches on

the cervical glands can be seen. Then, an acetic acid solution is applied to the cervix, and the presence of an epithelial reaction is observed.

white reaction test lasts approximately 3 minutes, and a series of images are obtained every 30 seconds. In a recent review, it was noted that the main obstacle to the development of colposcopy image analysis methods is the lack of large-scale, publicly available and multistate dataset.

A multistate dataset is critical for developing and validating machine learning systems for cervical cancer screening.

Popular test for Cervical cancer detection in the developed countries are HPV test, that is a DNA based test that detect cancer by associating it with specific HPV type and PAP smear test, that is inspections of the sample of cervix images under microscope.
But due to high cost of such test these are not much popular in developing and under developed countries. In developing countries Digital coloscopy test are used for Cervical cancer but that require a highly trained and experienced medical expert but they are not available in such countries.

LITERATURE REVIEW AND SURVEY

In this study, detailed review on machine learning and deep learn approaches used to identify the cervical cancer is studied.

Table I Literature survey on cervical cancer detection using Deep Learning

Author name	Methods used	Description
Zaid Alyafeai, Lahouari Ghouti, A Fully-Automated Deep Learning Pipeline for Cervical Cancer Classification, Expert Systems With Applications (2019) [1]	YOLO, Modified GoogLeNet image classifier model, CNN	Author purposed a fully automated deep learning pipeline approach for the detection of cervix regions and classification of cervical tumors. That is implemented in four modules as follows: Cervix Detection Module: that uses yolo and modified GoogLeNet module for detection of the cervical area. Roi Pre-Processing and Data Augmentation module: in this module image is standardized and some augmented images are generated for better performance of deep learning model Automatic Feature Extraction Module: A lightweight convolutional model is proposed to automatically extract features from the cervigram RoI images. Purposed model uses the standard RGB color space instead of hand-crafted features Cervical Cancer Classification Module: Once the automatic features are extracted, they are flattened into 128-dimensional feature vectors. The flattened feature vectors are processed through a logistic layer to produce a probability score about the presence or absence of cervical cancer
Abhilash Nandy, Rachana Sathish, Debdoot Sheet, IDENTIFICATION OF CERVICAL PATHOLOGY IN COLPOSCOPY IMAGES USING ADVERSARIALL	CNN, deep learning methods	Propose a method of applying the concept of deep learning and computer vision in order to automate the problem of cervical cancer screening using specular photographs of cervices. The cervical images are pre-processed by segmenting the region of interest in the cervical images using a Cervical Cancer Screening.

Y TRAINED CONVOLUTIONAL NEURAL NETWORKS [2]		The images are then classified using a convolutional autoencoder based framework. due to the shortage of the number of available samples, author adopt adversarial training, by adding a discriminator to the autoencoder architecture, thus making it an adversarial autoencoder.
KELWIN FERNANDES, JAIME S. CARDOSO, AND JESSICA FERNANDES Automated Methods for the Decision Support of Cervical Cancer Screening Using Digital Colposcopies [3]	Mathods of image processing,	Author explained core research lines surrounding the automated analysis of digital colposcopies and built a topology of problems and techniques, including their key properties, advantages, and limitations. Main tasks of detection of cervical cancer Quality assessment and enhancement of digital colposcopies Removal of specular reflections image normalization Segmentation of cervix tissues Image Registration Detection and characterization of abnormal tissues Classification of patient traits
SUXIANG YU, XINXING FENG, BIN WANG, HUA DUN, SHUAI ZHANG, RUIHONG ZHANG, AND XIN HUANG, Automatic Classification of Cervical Cells Using Deep Learning Method [4]	CNN (convolutional neural network), SPP (spatial pyramid pooling), inception module	Author compared four classification models: The first model was a 10-layer convolutional neural network (CNN). The second model was an advancement of the first model equipped with a spatial pyramid pooling (SPP) layer (CNN + SPP) to treat cell images based on their sizes. The third model replaced the CNN layers with the inception module (CNN + Inception) in first model. The fourth model incorporated both the SPP layer and the inception module into the first model (CNN + inception + SPP). The performances of the four models are estimated and compared by using the same testing data and evaluation index. The testing results demonstrated that the fourth model yields the best performance

Yao Yua, Jie Mab, Weidong Zhaob, Zhenmin Lic , Shuai Dinga* MSCI： A multistate dataset for colposcopy image classification of cervical cancer screening [5]	Prepared MSCI dataset, Hand crafted method, Deep learning method	MSCI dataset consist of colposcopy images of different grades of precancerous lesions (normal, CIN1, CIN2/3) and images of each grade include three states: acetic acid reaction, green filter, and iodine test. Hand -crafted method to extract the shape, color, texture, and gradient explicit feature of the colposcopy image. Deep Learning method is to extract the global depth feature of the colposcopy image based on deep learning method, including convolutional neural network.
KURNIANINGSIH 1, (Senior Member, IEEE), KHALID HAMED S. ALLEHAIBI2, LUKITO EDI NUGROHO3, (Member, IEEE), WIDYAWAN3, LUTFAN LAZUARDI4, ANTON SATRIA PRABUWONO5, (Senior Member, IEEE), AND TEDDY MANTORO6, (Senior Member, IEEE) Segmentation and classification of Cervical cells using Deep learning [6]	The Herlev pap smear dataset-CNN, k-CNN and SVM	The Herlev pap smear dataset collected by Herlev University Hospital (Denmark) and the technical University of Denmark of 917 images into 7 classes and performed CNN, performed KNN and SVM classifier having accuracy of above 90%.

DATASET

We have used dataset provided jointly by Intel and MobileODT companies. This dataset was made public in machine learning competition hosted by google Kaggle portal. This dataset contains images collected from women having no cervical cancer. This dataset contains three types of images based on the Locations of Different transformation zone. Images are classified as TYPE_1, TYPE_2, TYPE_3.

- TYPE_1 image:
  - Has Completely ectocervical components
  - Fully visible
  - Small or large

- TYPE_2 image:
  - Has endocervical components
  - Fully visible
  - May have ectocervical component which may be large or small

- TYPE_3 image:
  - Has endocervical component
  - Is not fully visible
  - May have ectocervical component which may be small or large

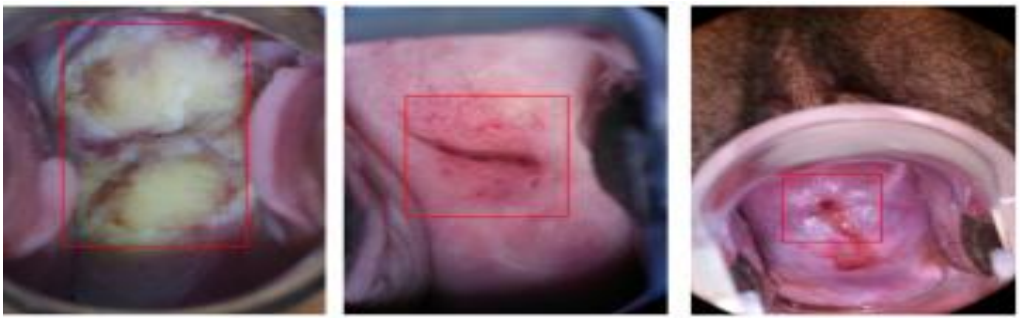

Figure 2 Types of Cervices (a) TYPE-1 (b) TYPE-2 (c) TYPE-3

PREPROCESSING

The images provided in the dataset are of different size hence, all images are resized to 512X512. For image enhancement we have Used AGCCPF ("Adaptive Gamma Correction with Color Preserving Framework") [7], This method enhances the contrast and brightness of given image using the gamma correction and weighted probability distribution of luminance pixels. This method doesn't affect image's visual and color information.

Then image is resized to 224X224 for training the model.

All pixel values are rescaled in range (0-1).

For data augmentation we applied:

rotation range = 30 (Image rotation randomly in range (+-) 30^0)
width shift range = 0.2 (Image is shifted randomly in range 20 % of width)
height shift range = 0.2 (Image is shifted randomly in range 20 % of Height)
shear range = 0.2 (Image is skewed randomly in range 20%)
zoom range = 0.2 (Image is Zoomed randomly in range 20%)

Dataset Split:

Dataset is splinted randomly by stratified sampling.
Training dataset:
Training dataset contain 80% of total images.
This is divide in 80 : 20 in model training and model validation dataset.
Testing dataset:
Testing dataset contains 20% images.

Table 1 Dataset Split

	TYPE_1	TYPE_2	TYPE_3	Total
Training Dataset	921	2780	1552	5253
Validation Dataset	231	696	388	1315
Testing Dataset	288	870	486	1644
Complete Dataset	1440	4346	2426	8212

METHOD OVERVIEW

In every model we have used MobileNet, VGG16 and DenseNet121 as classification base and used different classification layer for classifying the images in TYPE_1, TYPE_2, TYPE_3.

Classification Base Layer:

VGG16:

VGG16 focuses on having convolution layers of 3x3 filter with a stride 1 and always used same padding and maxpool layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture.

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	224 x 224 x 3	-	-	-
1	2 X Convolution	64	224 x 224 x 64	3x3	1	relu
	Max Pooling	64	112 x 112 x 64	3x3	2	relu
3	2 X Convolution	128	112 x 112 x 128	3x3	1	relu
	Max Pooling	128	56 x 56 x 128	3x3	2	relu
5	2 X Convolution	256	56 x 56 x 256	3x3	1	relu
	Max Pooling	256	28 x 28 x 256	3x3	2	relu
7	3 X Convolution	512	28 x 28 x 512	3x3	1	relu
	Max Pooling	512	14 x 14 x 512	3x3	2	relu
10	3 X Convolution	512	14 x 14 x 512	3x3	1	relu
	Max Pooling	512	7 x 7 x 512	3x3	2	relu

Figure 3 VGG16 Architecture

MobileNet:

Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1

Figure 4 MobileNet Architecture

DenseNet:

DenseNet (Dense Convolutional Network) is an architecture that focuses on making the deep learning networks go even deeper, but at the same time making them more efficient to train, by using shorter connections between the layers. DenseNet is a convolutional neural network where each layer is connected to all other layers that are deeper in the network, that is, the first layer is connected to the 2nd, 3rd, 4th and so on, the second layer is connected to the 3rd, 4th, 5th and so on.

Layers	Output Size	DenseNet-121
Convolution	112×112	
Pooling	56×56	
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56	
	28×28	
Dense Block (2)	28×28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28	
	14×14	
Dense Block (3)	14×14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$
Transition Layer (3)	14×14	
	7×7	
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$

Figure 5 DenseNet Architecture

Base Model 1:

In Base model 1 we have used transfer learning; we have used the pretrained weights from the ImageNet for the classification base and applied flatten layer on feature map extracted from the classification base and used dense layer and then SoftMax layer for classifying the image.

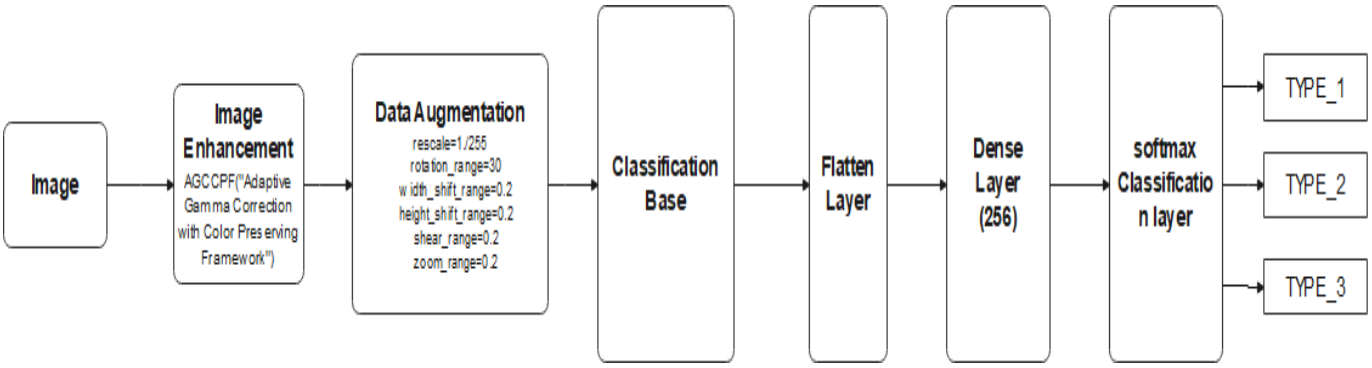

Figure 6 Base Model - 1 Architecture

Base Model 2:

In Base model 2 we have used transfer learning; we have used the pretrained weights from the ImageNet for the classification base and applied GlobalAveragePolling2D on feature map extracted from the classification base and then SoftMax layer for classifying the image.

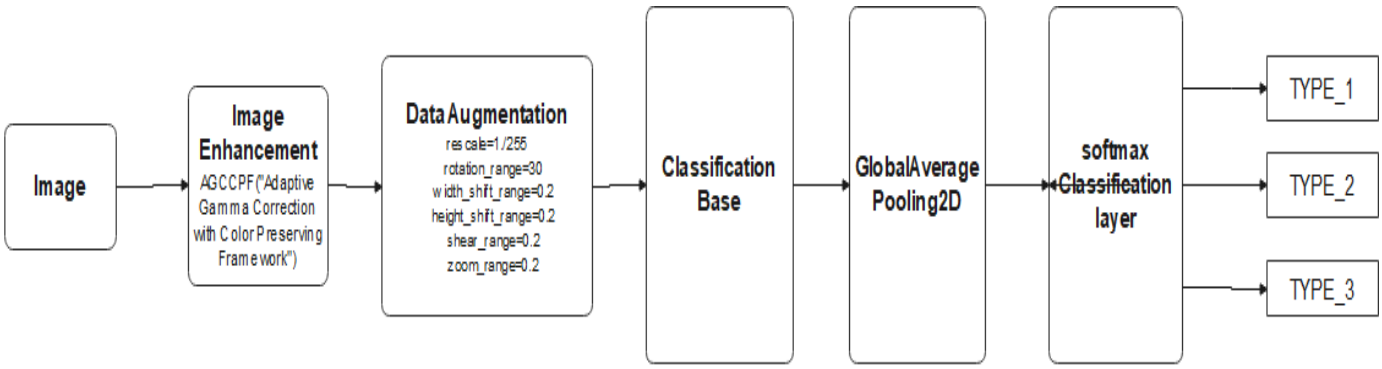

Figure 7 Base Model - 2 Architecture

Purposed Model:

In our purposed model we have used two classification bases VGG16 and DenseNet121 to extract the feature map from the image. First input layer is passed in both classification base layers parallelly and then these feature maps are passed separately through global average polling layer that is connected to a dense layer. Then output of both dense layers are concatenated by concatenation layer that is passed to a SoftMax layer for classifying the image.

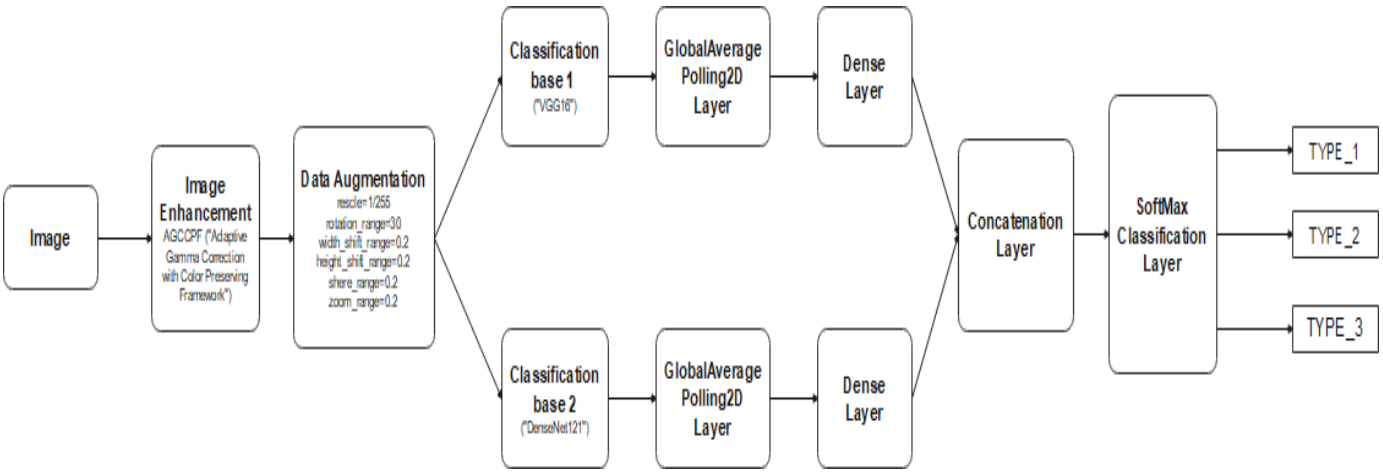

Figure 8 Purposed Parallel Model Architecture

LOSS FUNCTION AND EVALUATION MATRICES

Loss function:

Categorical cross entropy is used for calculating the loss of the classification. Categorical cross entropy is defined as:

Categorical cross entropy = $\sum_{i=1}^{n} t_i \log(p_i)$

Where t_i is true label and p_i is SoftMax probability for the ith class.

Accuracy:

Accuracy is most intuitive performance measure. Accuracy is ratio of correctly classified images and total images.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN}$$

TP = True positive
TN = True Negative
FP = False Positive
FN = False Negative

Recall (Sensitivity):

Recall is the ratio of correctly predicted images and actual images in the class.

$$\text{Recall} = \frac{TP}{TP+FN}$$

Precision:

Precision is ratio of the correctly predicted images of that class and total images predicted as that class.

$$\text{Precision} = \frac{TP}{TP+FP}$$

TRAINING AND RESULTS

We trained all the models using RMSPROP optimizer (Gradient based optimizer) with learning rate of 0.00001. we trained the models for 50 epochs with 260 steps with batch size of 20 image and 60 step of validation with batch size of 20 images.

Results:

Table 2 Results

Model	Validation			Testing		
	Accuracy	Recall	Precision	Accuracy	Recall	Precision
Base Model 1 (VGG16)	75.08	74.75	75.70	74.57	74.39	74.84
Base Model 2 (VGG16)	76.08	75.58	76.86	75.88	75.33	76.04
Base Model 1 (MobileNet)	70.17	69.25	71.03	72.26	71.16	72.71
Base Model 2 (MobileNet)	71.42	68.42	73.43	72.99	70.80	74.66
Base Model 1 (DenseNet)	70.17	69.17	71.06	71.53	70.49	72.39
Base Model 2 (DenseNet)	77.17	76.58	77.62	76.21	75.48	76.74
Purposed Model	78.33	77.25	79.64	76.82	75.91	77.61

Confusion Matrix:

185	69	34
37	724	109
10	122	354

Training Graph:

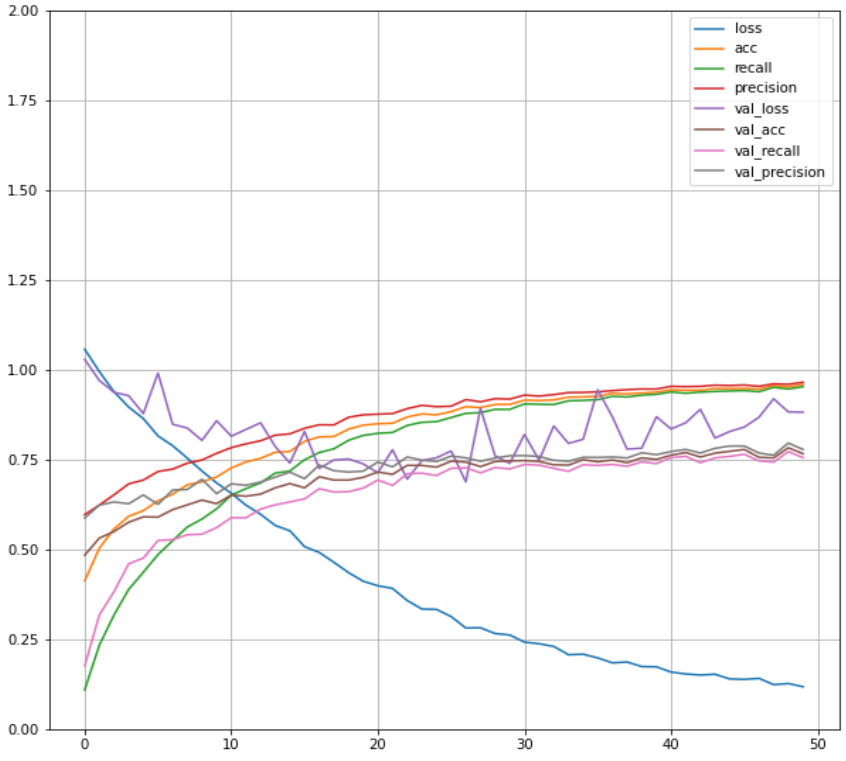

Figure 9 Training Graph

By the base model 1 and 2 we are able to see that the flattening of the feature map and then classifying them is not best suited for the images where our object in the image is not uniform and placed at some certain locations. In that case the weights of the multiple links have to update as the position of the object change in our image that led to high validation losses. Instead of that if we use global average pooling layer then we are taking average of the layer of the features map that gives us the 1-D array of feature map in which only the object surrounding weights gets update and this help in classifying the image having object in different location in the image. This we have used in our purposed model we have used advantage of multiple feature maps by providing our image parallelly to two feature extraction layer and then applying the classification on the output of both the feature maps output.

CONCLUSION

we can implement segmentation techniques of cervix region and then apply classification for improving the performance and accuracy. For segmentation we will get help from some medical expert for annotation of some of the images for creating a segmentation model. Screening process undergone for cervical cancer manually has higher issues of producing false negative rates as it requires high experience and that lack in developing countries. Hence an alternate method came into existence called automated cervical cancer detection to increase accuracy for testing cervical cancer. Better performances were shown by various researchers in classifying normal cells and abnormal cells by suggesting new approaches for segmentation or classification or feature extraction or in all. However, still miles of research have to be carried out in this domain to improve the level of accuracy, speed and storage cost.

REFERENCES

[1] Zaid Alyafeai, Lahouari Ghouti, A Fully-Automated Deep Learning Pipeline for Cervical Cancer Classification, Expert Systems with Applications (2019), doi: https://doi.org/10.1016/j.eswa.2019.112951

[2] Abhilash Nandy, Rachana Sathish, Debdoot Sheet, IDENTIFICATION OF CERVICAL PATHOLOGY IN COLPOSCOPY IMAGES USING ADVERSARIALLY TRAINED CONVOLUTIONAL NEURAL NETWORKS

[3] KELWIN FERNANDES, JAIME S. CARDOSO, AND JESSICA FERNANDES Automated Methods for the Decision Support of Cervical Cancer Screening Using Digital Colposcopies

[4] SUXIANG YU, XINXING FENG, BIN WANG, HUA DUN, SHUAI ZHANG, RUIHONG ZHANG, AND XIN HUANG, Automatic Classification of Cervical Cells Using Deep Learning Method

[5] Yu Y, Ma J, Zhao W, Li Z, Ding S, MSCI: A multistate dataset for colposcopy image classification of cervical cancer screening, International Journal of Medical Informatics (2020), doi: https://doi.org/10.1016/j.ijmedinf.2020.104352

[6] KURNIANINGSIH, KHALID HAMED S. ALLEHAIBI, LUKITO EDI NUGROHO, WIDYAWAN, LUTFAN LAZUARDI, ANTON SATRIA PRABUWONO AND TEDDY MANTORO Segmentation and Classification of Cervical Cells Using Deep Learning
7

[7] BHUPENDRA GUPTA, MAYANK TIWARI 5 INDIAN INSTITUTE OF INFORMATION TECHNOLOGY, DESIGN & MANUFACTURING JABALPUR, MP, INDIA