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Categorization of Cancerous Cervical Cells Using Convolutional Neural Networks and Deep Learning Techniques

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***ABSTRACT*—A precise categorization of abnormal cervical cells is critical but difficult. Traditional methods rely on manual or engineered features, while convolutional neural networks (CNN) use deep learning. Prior CNN models didn't consider cell morphology, so this study proposes a CNN method that combines appearance and morphology. The cervical cell dataset was trained with adaptively re-sampled image patches. Several pre-trained CNNs were fine-tuned and evaluated on the Herlev cervical dataset with a five-fold cross-validation. The proposed method achieved higher accuracy by adding morphological information to appearance-based CNN learning, with the best model achieving accuracies of 80%, 70%, 54% and 21% for two-class, four-class, and seven-class classification tasks. Combining morphology with appearance improves classification performance, but the task remains challenging.**

***Keywords*— Fine-grained classification, cell morphology, deep learning, Pap smear, Herlev dataset.**

I. INTRODUCTION

Cervical cancer is a common and deadly disease among women, mainly caused by human papillomavirus (HPV) infections that lead to cell dysplasia and abnormal changes. Pap smear is an effective screening test for early detection and prevention of cervical cancer, but it requires manual screening of abnormal cells, which is complex and prone to errors, especially in developing countries where screening is not widely available. To overcome these challenges, automation-assisted reading systems have been developed, which use automated image analysis techniques to identify potentially abnormal cells for further review and classification by cyto-screeners or cytopathologists, thereby improving efficiency and availability. The World Health Organization classification system identifies four stages of premalignant dysplastic changes in cervical cells: mild, moderate, severe dysplasia, and carcinoma in situ (CIS). While mild dysplasia is often just a manifestation of HPV infection, more severe stages pose a high risk of progression to cancer if left undetected and untreated. Early identification of dysplastic changes is crucial for preventing precancerous cell development. However, the task is challenging and subjective, and misclassification can lead to unnecessary biopsy or treatment delays. Therefore, fine-grained classification of cervical cells is essential in clinical diagnosis. While previous studies have focused on classifying cervical cells as normal or abnormal, this is not sufficient for diagnosis. Morphological features have been extensively used in computerized cell image processing and pattern recognition for biomedical applications, including quantifying nuclei features for cancer cell cycle analysis, extracting features for hepatocellular carcinoma, and classifying blood cells. In automation-assisted reading systems for cervical cells, the process generally involves cell segmentation, feature extraction/selection, and cell classification.

The design and selection of features are crucial for the classification of cervical cells, particularly morphological features, which describe changes in size, shape, intensity, and texture when dysplastic changes occur. In a previous study, twenty morphology-related features were extracted for this purpose. An automated method based on morphological analysis was proposed in another study for detecting cell nuclei in pap smear images. These extracted features can be categorized into handcrafted and engineering features, but handcrafted features are limited by the restricted knowledge of cervical cytology.

Unlike traditional machine learning methods that rely on manually engineered features, deep convolutional neural networks (CNNs) have become increasingly popular due to their ability to learn multi-level features automatically from large datasets. This approach has been particularly successful in computer vision tasks. With the development of more powerful hardware, such as Graphics Processing Units (GPUs), CNNs have become deeper and more complex, leading to the introduction of various CNN models and their variants in recent years. This approach has the potential to improve feature selection and eliminate the redundancy of handcrafted features, as CNNs can learn directly from the raw data, without relying on prior knowledge.

There have been studies investigating the use of CNNs for directly classifying cervical cells based on their morphological features. In one study, a deep learning framework called DenseNet was used to directly classify cervical cells based on their morphological features extracted from pap smear images. The results showed that the proposed method achieved higher classification accuracy compared to other methods that used handcrafted features and traditional machine learning classifiers. In another study, a CNN-based method was proposed for the automatic classification of cervical cells into normal and abnormal categories, based on morphological features extracted from pap smear images. The method achieved high accuracy and sensitivity in detecting abnormal cells. These studies suggest that CNNs can effectively model morphological features for cervical cell classification, and may have the potential to improve the accuracy and efficiency of cervical cancer screening.

That sounds like an interesting approach! It seems like your method is addressing some of the limitations of previous studies by incorporating not only raw RGB information but also cell morphology information, and evaluating performance on a more challenging 4-class classification task. Can you provide more details on how the cytoplasm and nucleus binary masks are generated, and how they are combined with the RGB-channels of the cell image to form a five-channel image? And how did you ensure patient-level separation on the Herlev dataset? That's great to hear! It seems that incorporating morphological information into CNNs improves the classification performance of cervical cells. It's also good that patient-level cross-validation was performed to ensure the validity of the results. The high classification accuracies achieved by the CNN fed with both morphological and appearance information show the potential of this approach for improving cervical cell classification in clinical settings.

More investigation is needed for several problems by classifying Cervical cells –

1) The proposed method achieved significantly higher classification accuracy compared to the existing method, especially in the case of 4-class and 7-class classification tasks.

2) The study demonstrated the importance of incorporating morphological features into CNN-based classification models for cervical cells.

3) The study used a patient-level cell splitting approach for five-fold cross-validation, which better reflects the real clinical setting.

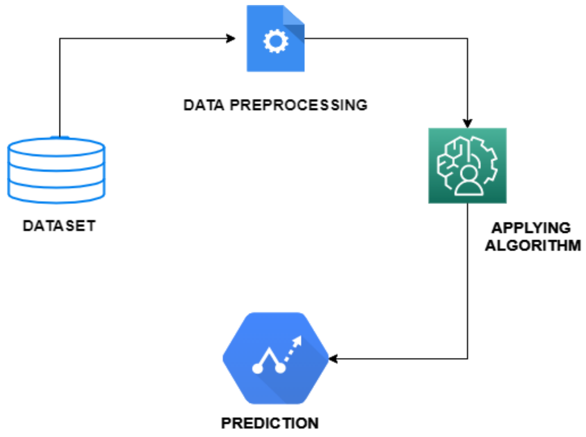


Fig 1.1: The overall flow-chart of our CNN framework classification

II. BACKGROUND STUDY

In the past many researchers have done a lot of work to find cervical cancer by classifying the cells. Because cervical cancer is highly treatable when detected early, researchers are developing better ways to detect precancer and cervical cancer. For example, fluorescent spectroscopy is the use of fluorescent light to detect changes in precancerous cervix cells. CNNs are often used for feature extraction in addition to their use as classifiers. By training a CNN on a large dataset, it learns to extract low-level to high-level features from the input data. These learned features can then be used as inputs to other classifiers, such as SVMs or decision trees, to improve their performance. Additionally, CNNs can be used to classify dynamic morphology of cells to represent different physiological states.

Correct, those are some limitations of the existing system. Let me elaborate on each point:

1) Using only raw RGB information may not be sufficient to capture all the relevant features of cervical cells. Additional information such as morphological features can be incorporated to improve classification accuracy.

2) While a 2-class classification task is useful for identifying normal vs. abnormal cells, a finer-grained classification (e.g.,4-class or 7-class) can provide more detailed information about the type of abnormality present in the cells.

3) While AlexNet was a breakthrough in image classification when it was introduced, newer and more powerful deep learning models have since been developed that may outperform AlexNet in certain tasks.

4) The previous method with five-fold cross-validation did not guarantee patient-level separation, which is important in clinical settings where it is crucial to avoid misclassification of cells from the same patient.

III. PROPOSED SYSTEM

The proposed system utilizes a CNN-based approach that combines cell image appearance with cell morphology for the classification of cervical cells in Pap smear. The method directly represents cell morphology using cytoplasm and nucleus binary masks, which are combined with raw RGB-channels of the cell image to form a five-channel image. Training data is sampled from a square image patch coarsely centered on the nucleus. The approach fine-tunes state-of-the-art CNN models pre-trained on the ImageNet dataset for 2-class (normal vs. abnormal), 4-class, and 7-class cervical cell classification based on deep hierarchical features.

The proposed system addresses the limitations of the existing system by evaluating the performance of 4-class and 7-class fine-grained classification of cervical cells and using different state-of-the-art CNN models for classification. Additionally, the system ensures patient-level separation on the Herlev dataset by performing five-fold cross-validation at the patient level. The inclusion of cytoplasm and nucleus masks as raw morphological information improves the overall classification accuracy of the system.

IV.EXPERIMENTAL STUDY

It appears that this study involved the use of cervical cell images that were processed to create binary masks of the cytoplasm and nucleus, as well as raw RGB channels. These images were then used as input data for convolutional neural networks (CNNs). The study evaluated the performance of state-of-the-art CNN models for both 2-class and 7-class classification tasks, and analyzed the results. More information about the specific methods and findings of the study would be needed to provide a more detailed explanation.

A. DATA PRE-PROCESSING

1)IMAGE PATCHING AND CELL MORPHOLOGY EXTRACTION

This section of the paper describes the data preprocessing steps that were taken in order to prepare the cervical cell images for analysis using convolutional neural networks. Image patch refers to a small, rectangular portion of an image that is extracted for analysis or processing. Image patches are often used in computer vision and image processing applications, such as object detection, recognition, and segmentation. By extracting small patches from an image, it is possible to focus on specific regions of interest and reduce the amount of data that needs to be processed. Cell morphology extraction refers to the process of analyzing and quantifying the shape, size, and other features of cells in biological samples. This can be done using various imaging techniques, such as microscopy, and can involve the use of image processing algorithms to extract relevant information from the images. Cell morphology extraction is important in many areas of biology and medicine, such as cancer research, drug discovery, and tissue engineering, where understanding the characteristics of cells can provide insights into their behavior and function.

And noted that cervical cells can be categorized into four classes based on TBS rules: normal, Low grade Squamous Intraepithelial Lesion (LSIL), High grade Squamous Intraepithelial Lesion (HSIL), and Carcinoma-in-situ (CIS). These different stages of cervical cytology abnormalities are associated with different characteristics of the nucleus.

Then described the strategy used to extract training samples for the CNN classification task. Specifically, they extracted image patches of size m×m centered on the nucleus centroid and including a certain amount of cytoplasm. This strategy allowed for embedding both nucleus size and contextual clues in the extracted patches.

Although there are methods for automated extraction of the nucleus, the authors chose to focus solely on the classification task and used the centroid of the ground truth mask of the nucleus to extract the image patches. The morphology of the nucleus and cytoplasm were obtained directly from the ground truth mask. Overall, this section provides important details on how the authors prepared the data for analysis using CNNs.

2) DATA AUGMENTATION

Data augmentation is the addition of new data artificially derived from existing training data. Techniques include resizing, flipping, rotating, cropping, padding, etc. It helps to address issues like overfitting and data scarcity, and it makes the model robust with better performance. The accuracy of CNNs can be improved and overfitting reduced through the use of data augmentation, which is crucial. As cervical cells are rotationally invariant, each cell image is rotated Nr times with an angle step of degree, while zero padding is employed to prevent regions lying outside the image boundary. Given the possibility of inaccurate detection of the nucleus centroid, the centroid of each nucleus is randomly translated Nt times (up to d pixels) to obtain Nt coarse nucleus centers. Subsequently, Nt patches of size mm are extracted from these locations. These patches simulate not only inaccurate nucleus center detection but also increase the number of image samples for CNNs. Other data augmentation techniques, such as color and scale transformations, are not used. To ensure a balanced distribution of positive and negative samples, we apply
a higher sampling proportion to the normal patches. For the 7-class task, similar sampling methods are utilized for balancing the proportions.

B. CONVOLUTIONAL NEURAL NETWORK ARCHITECTURES (CNN)

Convolutional Neural Networks (CNNs) are deep learning models that stack multiple stages of convolution, non-linearity, and pooling layers, followed by more convolutional and fully-connected layers. In our experiments, we focus on four CNN models: AlexNet, GoogLeNet, ResNet, and DenseNet. The input to the CNNs is an image patch with five channels, which includes two channels of binary masks of the cervical nucleus and cytoplasm, and three channels of raw RGB image. For performance comparison, the raw RGB image is used as the only input for some CNNs. The output layer of the CNNs consists of several neurons, each corresponding to one class. In our case, there are 2 and 7 neurons in the output layer for the 2-class and 7-class classification tasks, respectively. The backpropagation algorithm is used to optimize the weight parameters in CNNs by minimizing the classification error on the training dataset.

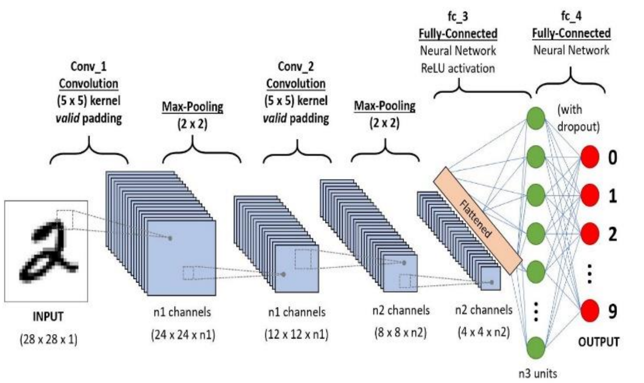


Fig 1.2: Convolutional Neural Network Architecture

AlexNet won the Image Net Large Scale Visual Recognition Challenge (ILSVRC) in 2012 and is a well-known CNN in computer vision. It has five convolution layers, three pooling layers, and three fully-connected layers. The ImageNet dataset consists of 1.2 million 256x256 images belonging to 1000 categories, and AlexNet achieved a top-5 classification error of 15.3%. GoogLeNet is a more complex and deeper CNN than AlexNet, and won the ILSVRC in 2014. GoogLeNet introduces a new module called "inception," which concatenates filters of different sizes and dimensions into a single new filter. Overall, GoogLeNet has two convolution layers, two pooling layers, and nine inception layers. Each inception layer consists of six convolution layers and one pooling layer, and GoogLeNet achieves a top-5 classification error of 6.67% on the ImageNet dataset challenge.

ResNet is about 20 times deeper than AlexNet and uses shortcut connections to jump over some layers, avoiding the problem of vanishing gradient. ResNet won the ImageNet ILSVRC in 2015 and has achieved impressive, record-breaking performance on many challenging image recognition, localization, and detection tasks. DenseNets are similar to ResNets, but with direct connections from any layer to all subsequent layers, which encourages feature reuse throughout the network. Moreover, DenseNets can achieve state-of-the-art performance with substantially fewer parameters and less computation than ResNet.

C. TRANSFER LEARNING

Transfer learning involves the fine-tuning of deep learning models that have been pre-trained on large-scale image datasets. In this study, due to the limited availability of cervical image data, pre-trained models from the ImageNet dataset are used as the foundation for each CNN architecture. Transfer learning is useful when the new task has limited data or when it is difficult or expensive to train a model from scratch. By using a pre-trained model as a starting point, transfer learning can save time and resources while still achieving good performance on the new task. There are several ways to implement transfer learning, depending on the specific application and the pre-trained model being used. One common approach is to fine-tune the pre-trained model by adjusting its parameters to better fit the new task. The first convolution layer and several task-specific full-connection layers are randomly initialized while the other network layers are transferred to our model. All of these layers are then jointly trained on our cervical cell dataset, with only the first convolution layer and the last several task-specific full-connection layers being trained from scratch. During testing, random-view aggregation and multiple crop testing methods are utilized.

V. IMPLEMENTATION

A. HERLEV DATASET

Implementation of this project is done using the Herlev Dataset. It consists of approximately 917 Cervical cell images. The cells have been carefully split to perform five-fold cross validation at the patient-level. The training set image has 7 different classifications namely.

Category	Class	Cell type
Normal	1	Superficial squamous epithelial
Normal	2	Intermediate squamous epithelial
Normal	3	Columnar epithelial
Abnormal	4	Mild squamous non-keratinizing dysplasia
Abnormal	5	Moderate squamous non-keratinizing dysplasia
Abnormal	6	Severe squamous non-keratinizing dysplasia
Abnormal	7	Squamous cell carcinoma in situ intermediate

Table 1: The Herlev Dataset

Four CNN Algorithms such as AlexNet, GoogLeNet, ResNet, DenseNet has been implemented in this project.

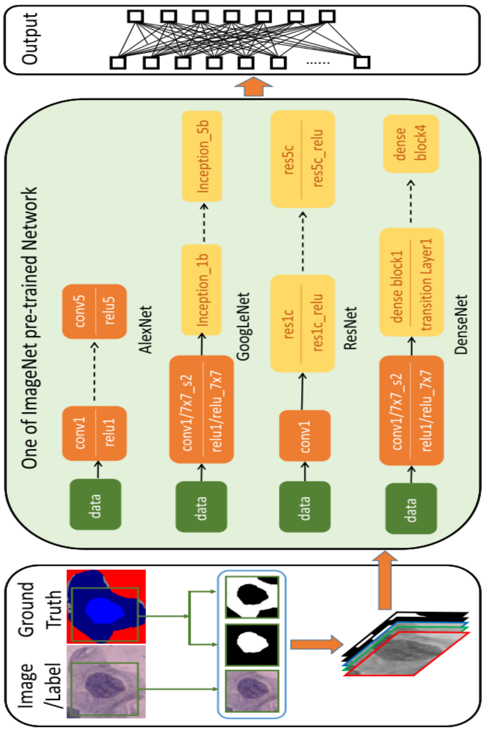


Fig 1.3: The overall flow-chart of our CNN framework for 7-class classification problem.

The dataset is publicly available and contains 917 images of cervical cells that were collected at the Herlev University Hospital using a digital camera and microscope. Each image has a resolution of 0.201 µm per pixel and contains a cervical cell with its segmentation of nucleus and cytoplasm, as well as a class label. The images were categorized into seven classes by two cytotechnicians and a doctor and were further classified into normal and abnormal categories. The dataset was augmented by performing rotations and translations on each image and up-sampling the images and segmentation masks to a size of 256×256×5 for transfer learning with a pre-trained CNN model. The image patches and masks were concatenated to create a five-channel dataset.

A. NETWORK ARCHITECHTURES

A study that evaluates the performance of different CNN models on two different classification tasks using two different input datasets. The CNN models used in the study are AlexNet, GoogLeNet, ResNet-50, and DenseNet-121, and they are pre-trained on the ImageNet classification dataset. The study compares the classification performance of the models on 2-class and 7-class classification tasks using three different input datasets: a raw RGB-channel dataset (CNN-3C), a two-channel dataset of nucleus and cytoplasm binary mask (CNN-2C), and a five-channel dataset (CNN-5C). The study also discusses the initialization of weights for the different models and reports that the AlexNet-T model has a slightly different configuration from the AlexNet-B model, with a reduced number of neurons in the fc6 and fc7 layers. Finally, the study reports that all models are implemented on the Caffe platform using two Nvidia GeForce GTX 1080 Ti GPUs with a total memory of 22 GB.

B. TRAINING AND TESTING THE IMAGES

The training images are 256 × 256 patches, and a 227 × 227 sub-patch is randomly cropped for AlexNet-T, while a 224 × 224 sub-patch is randomly cropped for the other networks. Stochastic Gradient Descent (SGD) is used to train the models for 30 epochs, with mini-batch sizes of 256, 32, 20, and 12 for AlexNet-T, GoogLeNet-T, ResNet-T, and DenseNet-T, respectively. The base learning rates are set to 0.01, 0.005, 0.01, and 0.01 for AlexNet-T, GoogLeNet-T, ResNet-T, and DenseNet-T, respectively, and are decreased by a factor of 10 every tenth epoch. The weight decay and momentum are set to 0.0005 and 0.9 for AlexNet-T and 0.0002 and 0.9 for the other networks. And the trained images are tested for further process.

D. METHODS EVALUATION

In this study include five-fold cross-validation on patient-level to ensure cells from the same patient are either in the training set or validation set, data augmentation after training/validation splitting, and performance evaluation metrics of sensitivity, specificity, accuracy, and area under ROC curve. For the 7-class problem, the confusion matrix is used to show the classification performance, while for the 4-class classification result, the 7-class result is aligned with TBS. The final performances of the models are obtained by averaging the results from the 5 validation sets.

C. OBJECTIVES

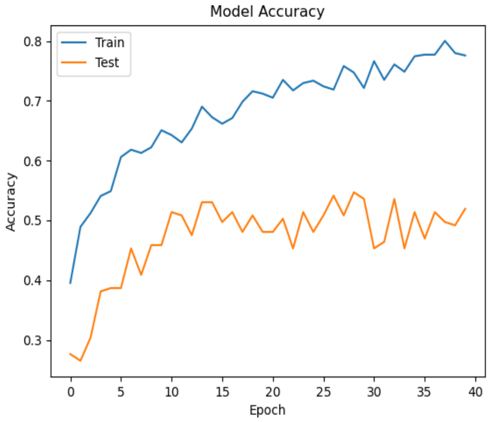
The main objective of the project is to provide safe treatments to identify cervical cancer at early stage for women. There are many techniques to identify and provide correct before it leads severe. For example, Screening helps detect abnormal cells in the cervix, which can develop into cancer. A Pap smear, also called a Pap test, is an exam a doctor uses to test for cervical cancer in women. Early detection may mean less treatment and less time spent recovering. The earlier cervical cancer is detected, the better your chance of survival.

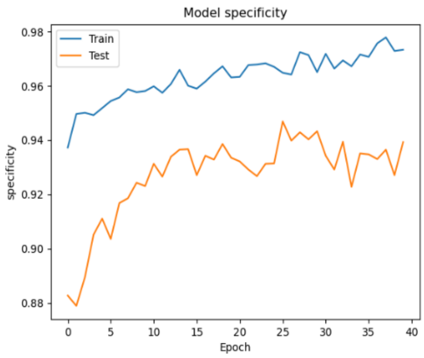
VI.RESULTS

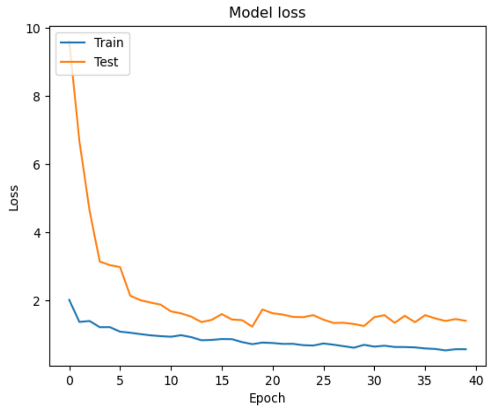
Implementation of this project is done using the Herlev Dataset. It consists of approximately 917 Cervical cell images. Four CNN Algorithms such as AlexNet, GoogLeNet, ResNet, DenseNet has been implemented in this project. Training is conducted for all four algorithms like GoogLeNet, ResNet, AlexNet and DenseNet algorithms as per the methodology specified previously.

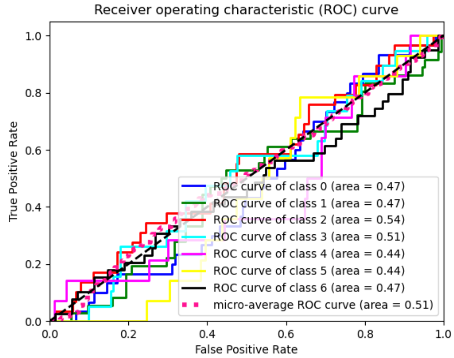
1) DenseNet Algorithm

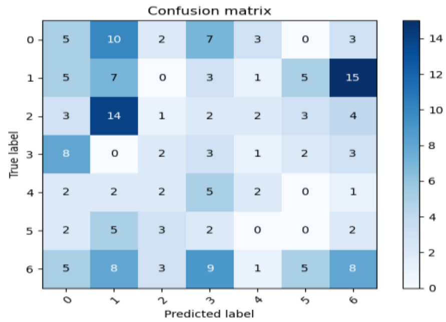
A DenseNet is a type of convolutional neural network that utilizes dense connections between layers, through Dense Blocks, where we connect all layers (with matching feature-map sizes) directly with each other. We achieved higher accuracy of 80% in this algorithm after training the dataset.





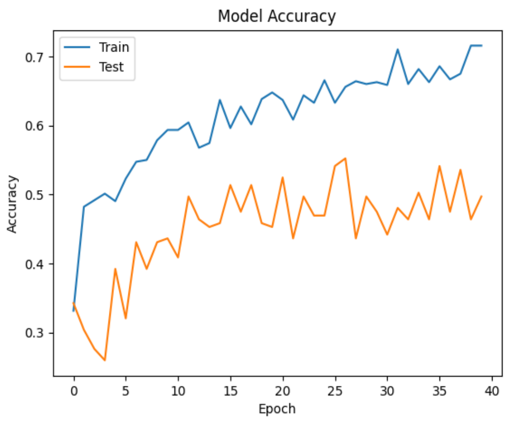


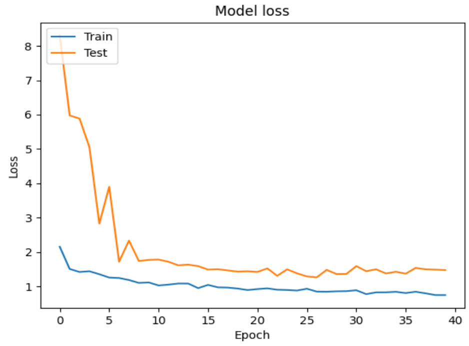


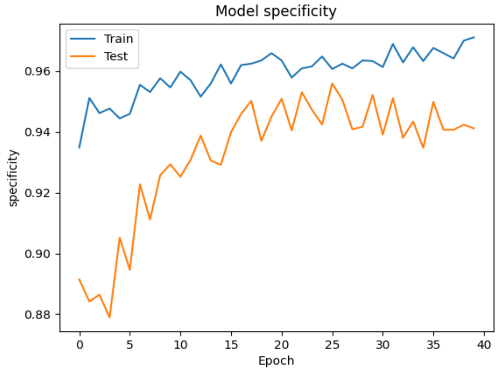


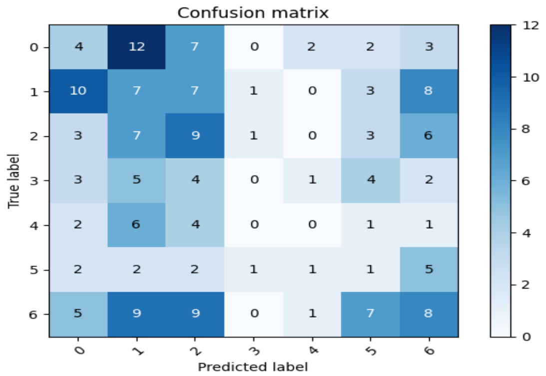
2) GoogleNet Algorithm

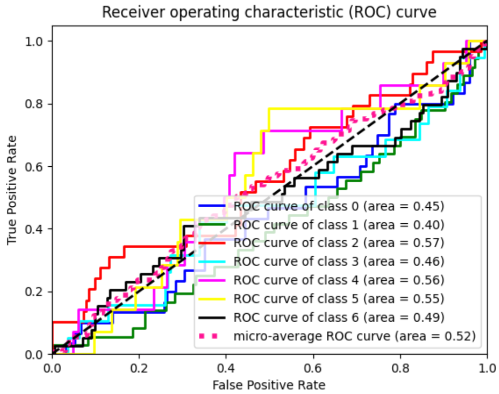
GoogLeNet is a type of convolutional neural network based on the Inception architecture. It utilizes Inception modules, which allow the network to choose between multiple convolutional filter sizes in each block. We achieved accuracy of 70% in this algorithm after training the dataset.





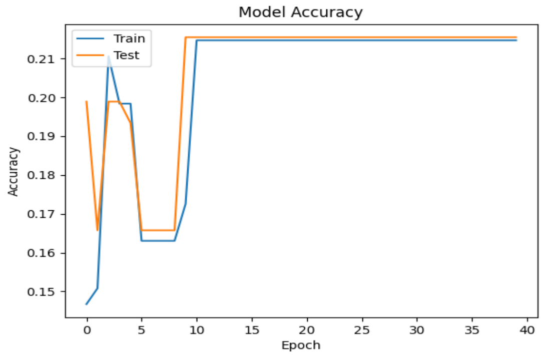


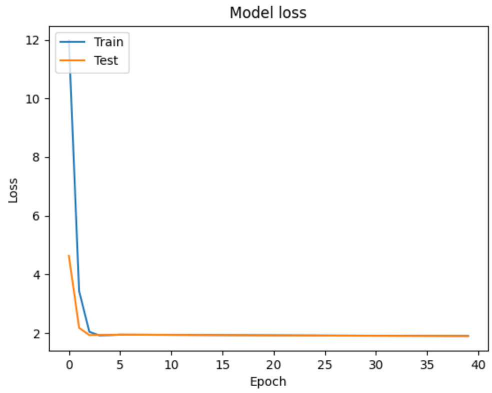


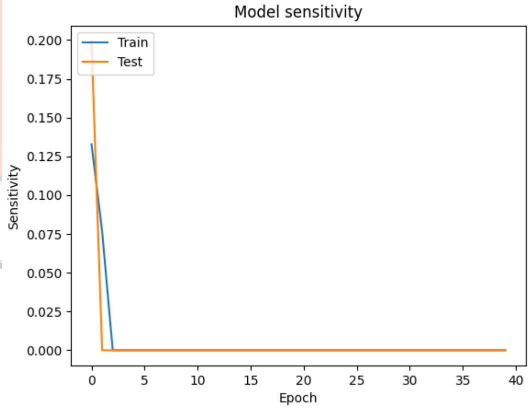


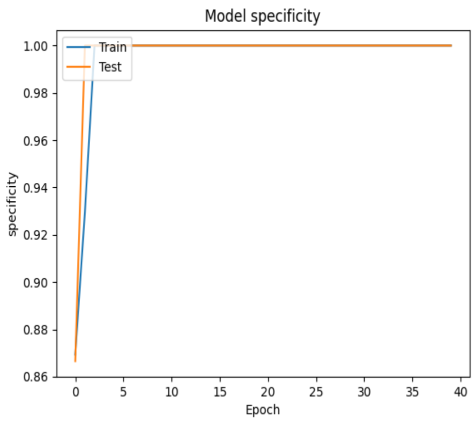
3) ResNet Algorithm

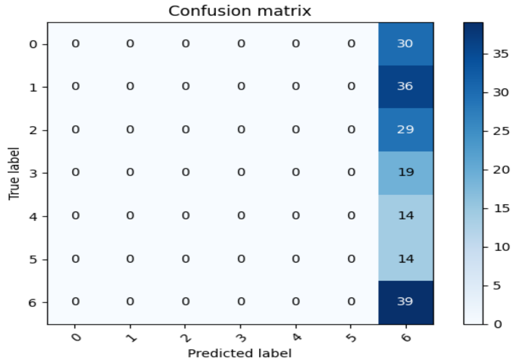
ResNet stands for Residual Network and is a specific type of convolutional neural network (CNN). We achieved accuracy of 21% in this algorithm after training the dataset.

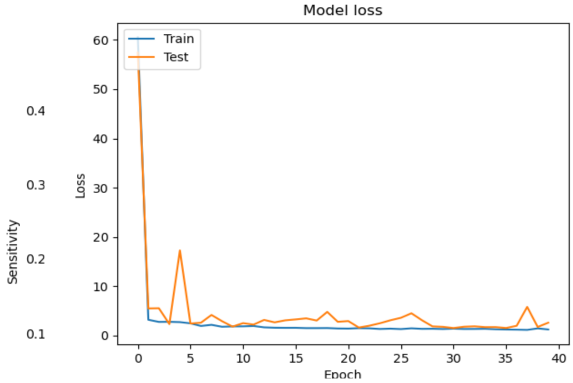


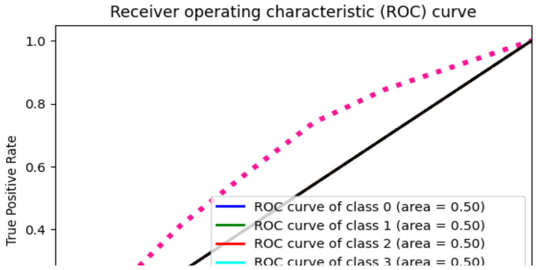


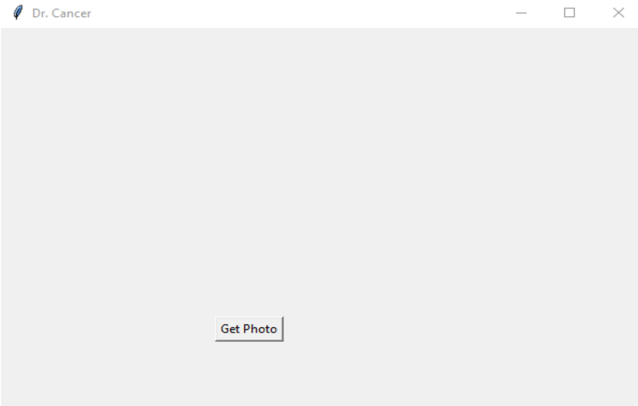


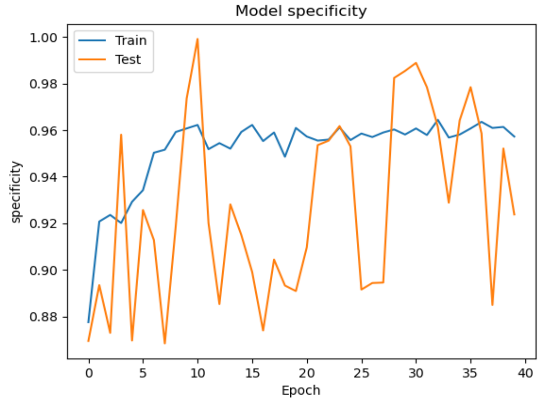








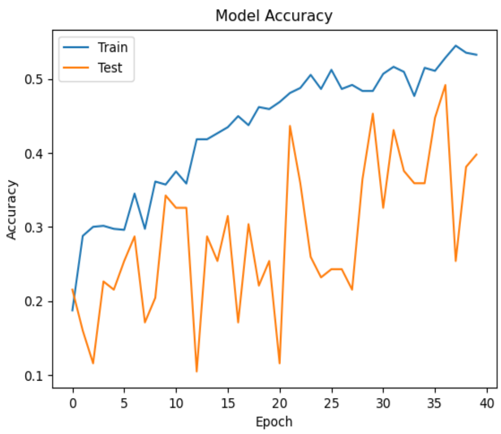


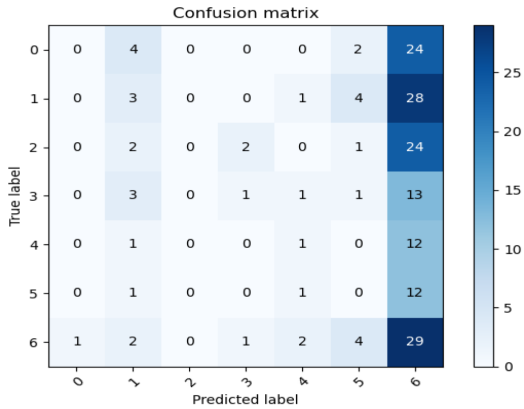


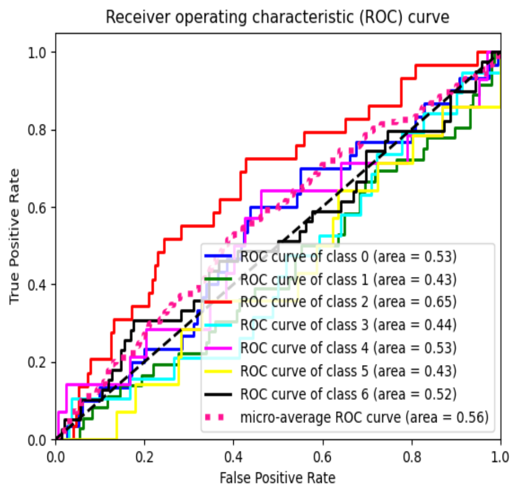
We used Tkinter for the front-end, where get a page or window of let's start. After that image selection will open where we can select

4) AlexNet Algorithm

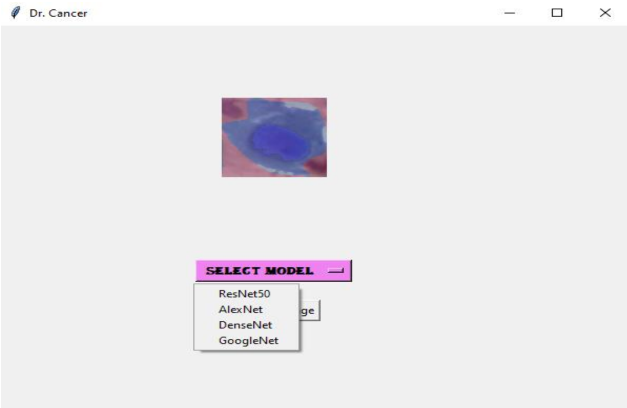
AlexNet is a classic convolutional neural network architecture. It consists of convolutions, max pooling and dense layers as the basic building blocks. We achieved accuracy of 54% in this algorithm after training the dataset.

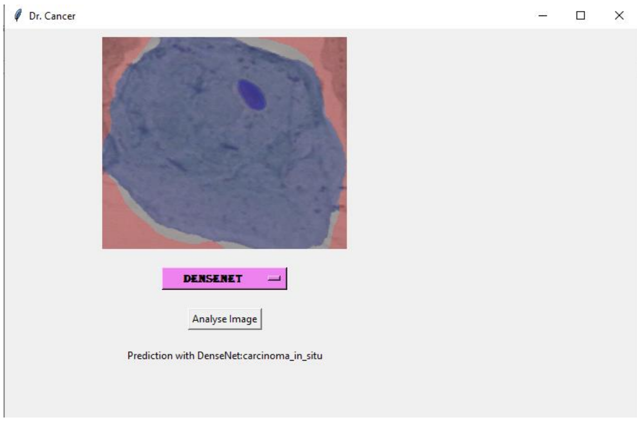


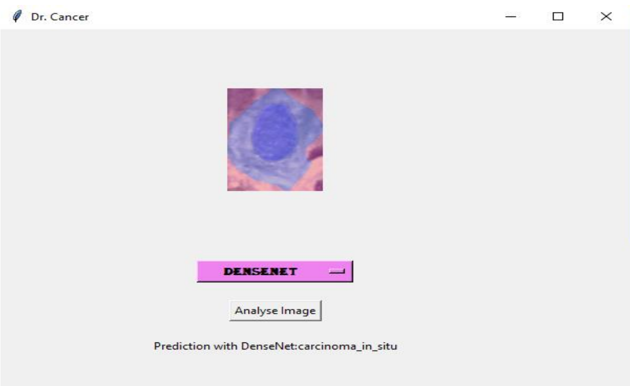




images of cervical cell by selecting the algorithm to check the presence of cancerous or not.







VII. CONCLUSION

This article introduces a novel method for fine-grained classification of cervical cells using a convolutional neural network (CNN) based on their appearance and morphology. In contrast to previous CNN-based methods that solely relied on raw image data as input, our approach employs a combination of raw image data and segmentation masks of the nucleus and cytoplasm. Our method involves extracting cell image/mask patches that are coarsely centered on the nucleus, transferring features from a pre-trained model to a new model that is fine-tuned on the cervical cell image dataset, and producing the final network output. To assess performance, we trained several state-of-the-art CNN networks (including AlexNet, GoogLeNet, ResNet, and DenseNet) and compared their results. Our findings indicate that using the combination of raw RGB data with segmentation masks of nuclei and cytoplasm as network input can achieve better performance in fine-grained classification of cervical cells. However, despite the promising initial results, fine-grained cervical cell classification via deep learning remains a challenging task for achieving high precision diagnosis. Additionally, the effects of automated segmentation of nucleus and cytoplasm on classification performance require further analysis in future studies.

VIII. REFERENCES

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