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User Interface Application for Cancer Classification using Histopathology Images

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Abstract : User interface for cancer classification system is a software application with clinician's friendly tools and functions to diagnose cancer from pathology images. Pathology evolved from manual diagnosis to computer-aided diagnosis with the help of Artificial Intelligence tools and algorithms. In this paper, we explained each block of the project life cycle for the implementation of automated breast cancer classification software using AI and machine learning algorithms to classify normal and invasive breast histology images. The system was designed to help the pathologists in an automatic and efficient diagnosis of breast cancer. To design the classification model, Hematoxylin and Eosin (H&E) stained breast histology images were obtained from the ICIAR Breast Cancer challenge. These images are stain normalized to minimize the error that can occur during model training due to pathological stains. The normalized dataset was fed into the ResNet-34 for the classification of normal and invasive breast cancer images. ResNet-34 gave 94% accuracy, 93% F Score, 95% of model Recall, and 91% precision.

Key Words : Deep Learning, Histopathology images, ResNet-34, Digital Pathology, AI, CAD

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1. Introduction

Breast cancer is the condition in which cells in the breast change and divide uncontrollably. There are mainly two types of breast cancer: In Situ carcinoma and Invasive carcinoma. Breast cancer diagnosis passes through different stages; breast exam, mammography, sonography, biopsy, and then results. Examination of the biopsy specimen is the main block of the diagnostic workflow because it detects diseased areas in the specimen. Generally, pathologists use the microscopic method for the examination of the specimen which is a time-consuming procedure. There is a need for an automated cancer classification system that can help pathologists in an accurate diagnosis of cancer. About 81% of breast cancers are invasive, invasive breast cancer is the outgrowth of cancer cells through the walls of the breast glands and ducts. The primary task in developing the automated breast cancer detection system is to classify breast images into normal and invasive images.

1.1 Related Work

This section explained some of the standard methodologies for breast cancer detection using histopathology images. Most of the research on breast cancer detection comprises classification and segmentation models using convolution neural networks.

Current applications for the diagnosis of breast histology images are diagnostic and prognostic.[4] Deep learning techniques have been used to extract features from the histopathology images using deep CNN, Inception-V3, and Inception ResNet-V2 architectures using the transfer learning approach.[5] Benefits of transfer learning over training from scratch were demonstrated by [6] using three pre-trained networks VGG16, VGG19, and ResNet50 for the classification of breast histology images. A finetuned VGG16 pre-trained model gave an accuracy of 92.06% with logistic regression while a full trained model had an accuracy of 64.40%. These results influenced us to use transfer learning for training a model instead of training the model from scratch. As it will save time and improve classification results. H&E-stained breast histology images were classified using the ICIAR dataset by applying strong data augmentation and pre-trained CNN models. For the 4-class classification task, [7] report 87.2% accuracy, and for 2-class classification[7] report 93.8% accuracy. Patch Based Classifier using CNN for the classification of ICIAR dataset was proposed using 2 class and 4 class classification model. This model works in two different modes: one patch in one decision (OPOD) and all patches in one decision (APOD). OPOD mode achieves patch-wise classification accuracy of 77.4% for 4 and 84.7% for 2-class classification model while APOD technique achieves image-wise classification accuracy of 90% for 4-class and 92.5% for 2-class classification.[8]

1.2 Motivation

We have reviewed past models for cancer diagnosis and selected ResNet-34 for our breast cancer classification system. The motivation behind using ResNet34 is resistance against vanishing gradient problems which is common in deep neural networks.

1.3 Contribution

AI−based disease diagnosis software can be added to the pathologist workstation PC that can perform the following tasks.

- Deal with slides of different types of stains.
- Process histology images with inbuilt annotation tools for normalization and training a deep learning model.
- Perform classification between cancer images and normal images.

1.4 Challenges

The main obstacles for training the deep learning network are following.

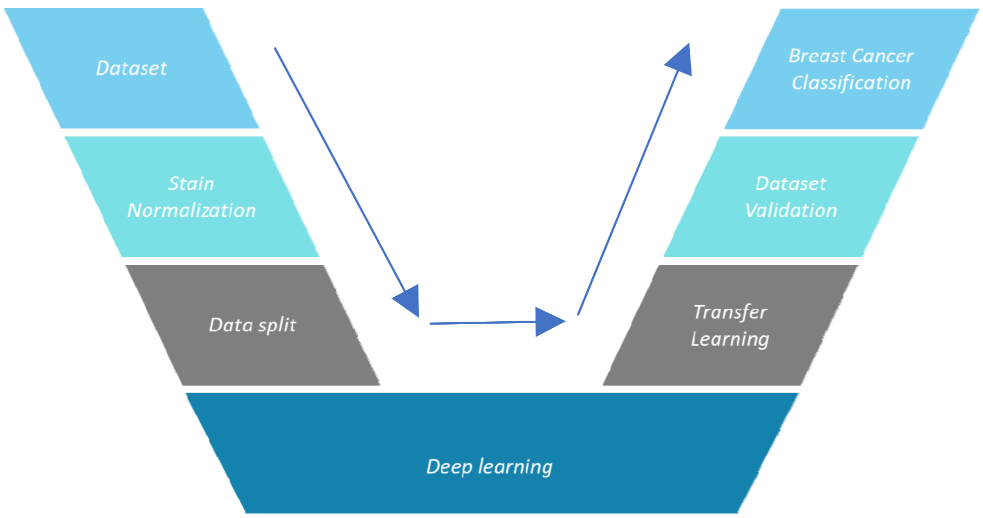
- To process the H&E−stained histopathology images because of their large size.
- We need to remove the stains present in histopathology images without decimating image size and quality.
- It is not possible to avoid decimation completely because of image processing losses during stain normalization, but we tried to reduce it as much as we could by applying efficient stain normalization techniques.

2. Materials and Methods

In this study, a two−class classification model was proposed to classify the breast histology dataset using the deep learning model ResNet−34. Fig.1 shows the methodology of the whole system's workflow using V− Diagram.

2.1 Dataset

100 normal and 100 invasive, hematoxylin and eosin (H&E) stained breast histology images were obtained from the ICIAR Breast Cancer challenge. Images are in "tiff" format of size 2048x1536 and pixel scale of 0.41㎛ x 0.42 ㎛.[9] This will be the input data for a deep learning model. To process this big size image dataset CPU memory was not enough,



[Figure 1] V−Diagram for developing the proposed system so we used GPU Nvidia K80 / T4 with 16GB memory and 12 GB RAM.

2.2 Stain Normalization

After attaining a dataset, the next step will be stain normalization. Because our dataset was stained with H&E stains to locate the diseased area during microscopic diagnosis. But these stains affect the performance of a deep learning model due to color variation between slides from different laboratories, so we decided to normalize these stains using a color normalization algorithm. Vahadane stain normalization algorithm was selected because of its ability to retain the image quality for better output. Vahadane algorithm can perform normalization with minimum loss as compared to other normalization techniques.[10]

2.3 Data Split

The normalized dataset was split for deep learning model training. ResNet-34 was trained with 50 normal and 50 cancer images that were placed in a training set while the validation set consisted of 25 normal and 25 cancer images and the test set also consisted of 25 normal and 25 cancer images, a total of 200 images.

2.4 Deep Learning Model

In this step, data is all ready to get into the deep learning model. For a deep learning model, we selected ResNet-34. Resnet34 is a 34 layer convolutional neural network that can be utilized as a state-of-the-art image classification model. In deep learning models, gradient decay is a common problem. It is hard for a network to converge when the depth of a model increased. Because with an increase in depth, loss between the convolutional layers also increases. ResNet-34 has resistance against vanishing gradient problems because it takes residuals from each layer and uses them in subsequent layers which makes it different from other deep learning models.

2.5 Transfer Learning

The process of learning the features from the previous model and transferring those learned features to the new model is called transfer learning. The transfer learning approach was selected for training the model instead of training the whole model from scratch because transfer learning saves time and improves model performance. Full trained ResNet-34 model was taken from PyTorch in which we froze the initial layers and only trained the last few layers with our dataset to make the prediction. This method has saved time and improved model performance.

2.6 Dataset Validation

After model training, the dataset has been validated with validation and testing set and gave the results in the form of cancer classification.

2.7 Breast Cancer Classification

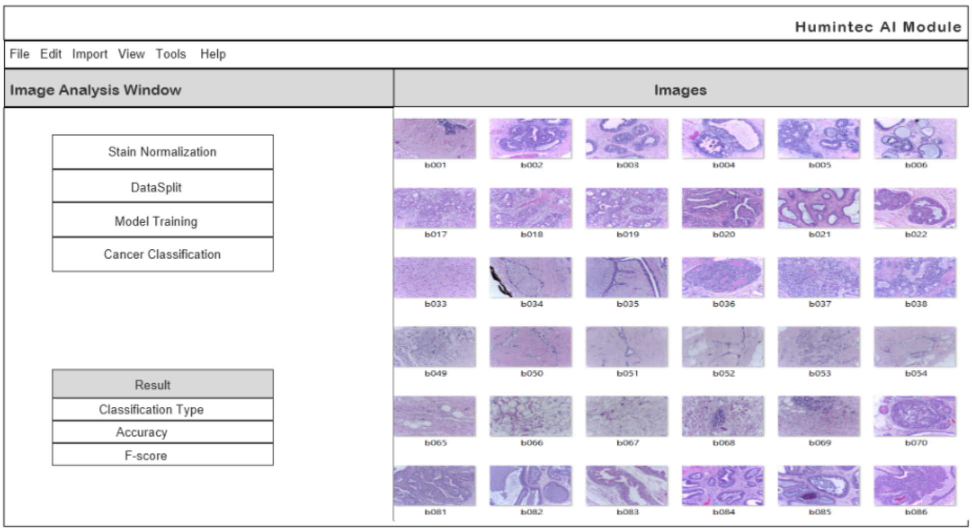
This model classified normal and invasive breast images. ResNet-34 gave 94% accuracy, 93% F Score, 95% of model recall, and 91% precision, with one false positive and two false negatives.

3. User Interface Design

After implementing an algorithm, there is a need for an application that doctors can use practically for disease diagnosis. Gradio python library was used to design the User Interface(UI) model for pathologists. There are separate modules for stain normalization, data split, model training, and cancer classification in the image analysis window. So, the clinician can import images in this application with the “import” tab and can access the desired image analysis modules with just one click. This way they can get the output in the “Result” tab in the form of classification, accuracy, and precision. The overview of UI is shown in Figure-2 User Interface Design.

4. Conclusion

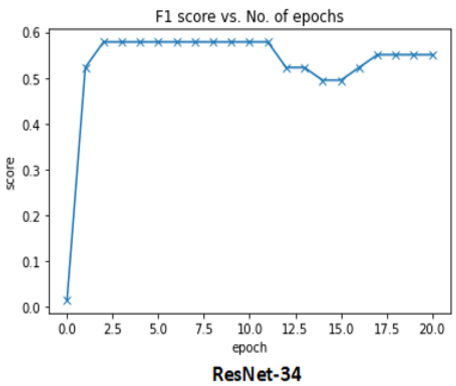
A cancer classification model with a user interface was designed for the ease of pathologists. This model provides an automated system for disease diagnosis. Now pathologists do not have to rely on a microscope for disease diagnosis but they can use AI applications for that purpose. This system will save doctors time and effort and also increase the number of patient's exams ratio. We proposed 2 class breast cancer classification system to classify normal and invasive breast histology images. ResNet34 gave an accuracy of 94% accuracy, 93% F Score, 95% of model Recall, and 91% precision shown in Table 1. This system can process, analyze, and classify 200 histopathology images of size 2048X1536 using 3.61 GB RAM in less than 5 minutes. The model was trained using pre-trained weights from Pytorch that have reduced training time as well as improved accuracy, F-Score, precision, and recall rate. The graph for F-score is in Figure-3. A confusion matrix is shown in Figure- 4 which shows one false negative and two false positives that is a negligible error for a deep learning model.



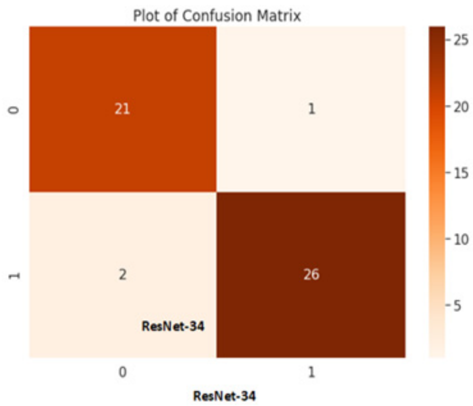
[Figure 2] User Interface Design

<Table 1> System Performance

ResNet34	Output
Accuracy	94%
F_score	93%
Model Recall	95%
Precision	91%
False Positive	1
False Negative	2



[Figure 3] Graphical Representation of System



[Figure 4] Confusion Matrix

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