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Internship Program- Deep Learning and Computer vison
Batch- December-January
Certificate Code- TCRIK01R51
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Technical Coding Research Innovation, Navi Mumbai,
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BREAST CANCER DETECTION

A Case-Study Submitted for the requirement of
Technical Coding Research Innovation

For the Internship Project work done during
DEEP LEARNING USING COMPUTER VISION INTERNSHIP PROGRAM

by
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Breast Cancer Detection Using Deep Learning

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Abstract **- Breast cancer is very frequent among women. Younger women don't often consider themselves at risk. However more than 5% of cases have been found in women under the age of 40. Mammography procedure is often used and is more efficient. However it would be much helpful if the cases were detected at an early stage. The aim of this paper is to identify breast cancer using deep learning. Using the Breast Histopathology Images dataset, we'll classify the presence of IDC (Invasive Ductal Carcinoma).**

Index Terms - Breast cancer · Deep learning · Machine learning · Histopathology.

I. Introduction

Breast cancer is mainly divided into ductal or lobular carcinomas which occur in the tissue of the breast..
The treatment for this type of cancer is usually determined by the size, stage, rate of growth and other characteristics of the cancer. Treatment for this particular cancer may include a combination of the following; surgery, hormonal drug therapy, chemotherapy, radiation and/or immunotherapy. Breast cancer accounts for 22.9% of all cancers in women worldwide. The primary risk factors that are associated with an increase of morbidity are female sex and older age. Research has shown that these negative side effects can lead to deterioration of lean body tissue, lowered functional capacity, weight gain, difficulty in sleeping, fatigue, nausea, pain, depression, poor body image, and lowered self-concept.

Breast cancer is detected using a variety of diagnostic methods. Magnetic resonance imaging (MRI), breast ultrasonography, mammography, positron emission tomography (PET), fine needle aspiration, and surgery are some of the typical modalities used to obtain tissue from a suspicious location (histopathological images), etc[2].

A number of clinical trials have found that the immunohistochemical and molecular classifications of breast cancer do not completely overlap[3]. The application of immunohistochemistry for the diagnosis of breast cancer subtypes was verified by the St Gallen International Expert Consensus in 2015 [4]). A comprehensive approach for reliable evaluation of cell morphological aspects is urgently necessary due to the significant heterogeneity in breast cancer and the poor predictive ability of histological classification.

II. Methodology

A. Google Colab

Google Colab is a free Jupyter notebook environment that runs entirely on the cloud and can be simultaneously edited by multiple people. Colab supports many popular machine learning libraries which can be easily loaded in your notebook. It also has GPU support which makes it easy to train huge models in a matter of minutes which can take hours when trained on CPU. Google colab can also access Google Drive. So, the dataset (as shown in Fig 1.) can be uploaded in the drive and the whole system will then work only on cloud.

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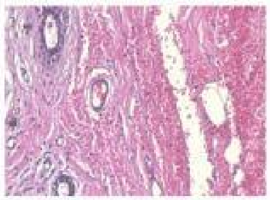
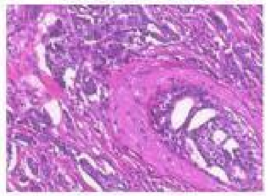
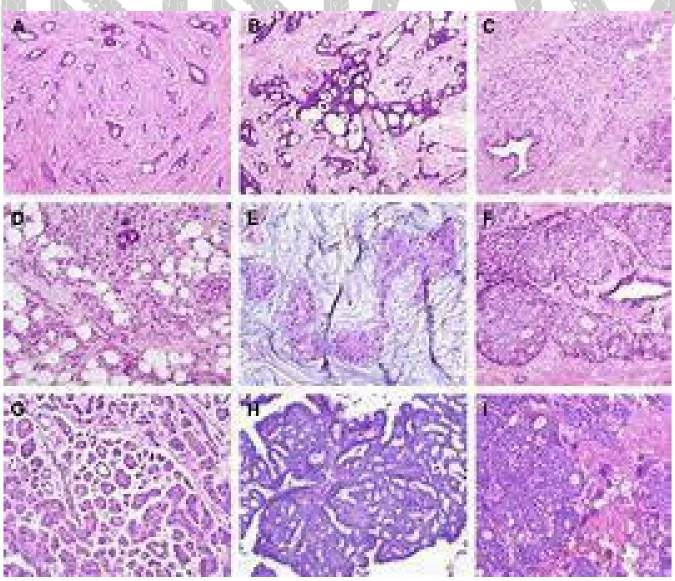



B. *Dataset*

In this study, the breast cancer dataset of microscopic images was utilized to evaluate the performance of a dataset containing 7,909 breast cancer biopsy images at different microscope magnifications. Each pathological image is a 700x460 pixel png format file with 3 RGB channels. Later, the dataset was stained with hematoxylin and eosin, and images were divided into two categories: malignant and benign. A total of 2480 samples were included, including four types of benign breast tumors, and four types of malignant tumors. In this study, 70% images were employed for training, while the remaining 30% were utilized for independent testing. Each type of image was allocated with a training set and a test image ratio of 7: 3. The most prevalent subtype of all breast cancers is Invasive Ductal Carcinoma (IDC). Pathologists often focus on the sections of a whole mount sample that contain the IDC when assigning an aggressiveness grade. As a result, delineating the exact regions of IDC within a whole mount slide is a frequent pre-processing step for automatic aggressiveness rating.



C. *Convolutional layer*

In deep learning, a convolutional neural network is a class of deep neural networks, that are typically used to recognize patterns present in images but they are also used for spatial data analysis, computer vision, natural language processing, signal processing, and various other purposes The architecture of a Convolutional Network resembles the connectivity pattern of neurons in the Human Brain and was inspired by the organization of the Visual Cortex. This specific type of Artificial Neural Network gets its name from one of the most important operations in the network: convolution. The first layer of a Convolutional Neural Network is always a Convolutional Layer. Convolutional layers apply a convolution operation to the input, passing the result to the next layer. A convolution converts all the pixels in its receptive field into a single value. For example, if you would apply a convolution to an image, you will be decreasing the image size as well as bringing all the information in the field together into a single pixel. The final output of the convolutional layer is a vector. Based on the type of problem we need to solve and on the kind of features we are looking to learn, we can use different kinds of convolutions.

C. Results

Using Imagenet Inception and Resnet pretrained models, the accuracy obtained is 91%. In the world of medical pathology, the diagnosis of breast cancer using digital/digitized histopathology photos is a watershed moment. Instead of manually lowering image size, an autoencoder can be used to improve the proposed method. From a method improvement standpoint, we can add spectrum imaging. As a result, we used ImageNet Inception and ResNet pre-trained models to set the weights of different layers in our proposed network. On the cancer pictures data set, we used last layer fine-tuning. As a result, while the final completely linked layer was updated continually, the ImageNet pre-trained weights were kept. Because the cancer data sets investigated here are huge and dissimilar to ImageNet, the whole layer fine-tuning was used to compare cancer classification accuracy with the last layer fine tuning.

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```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inception_resnet_v2 (Functi  (None, 3, 3, 1536)       54336736
 onal)

 global_average_pooling2d (G  (None, 1536)             0
 lobalAveragePooling2D)

 dense (Dense)               (None, 128)               196736

 batch_normalization_203 (Ba  (None, 128)              512
 tchNormalization)

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 54,534,113
Trainable params: 54,473,313
Non-trainable params: 60,800
_________________________________________________________________
```

D. Conclusion

When compared to traditional approaches, using a deep learning ResNet methodology with precise settings for cancer diagnosis is an effective and dependable strategy. The focus of this research was on using the presented frameworks to detect cancer. Various Inception and ResNet deep learning classifications are presented in this study, as well as the application of these ideas. Future research involving different deep learning semantic segmentation methods (e.g., U-net: convolutional networks for biomedical picture segmentation and DeepLab v3 is expected to assess and discuss the findings more thoroughly. This study's empirical findings helped researchers better comprehend deep learning in medical applications. The principles of the framework could be used for pathological analysis and computer-assisted diagnosis using medical imagery.

E. References

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