Object Detection and Segmentation in Histopathological Images using Deep Learning Approaches

[1]Dr. P M Shivamurthy, [2]Varshitha V, [2]Balasubramanyam S, [2]Shreyas H D, [2]Deekshith R
[1]Assistant. Professor, [2]Student,
[1,2]Computer Science and Engineering,
[1,2]JSS Science and Technology University, Mysuru, India.

Abstract: The purpose of this project is to solve the long unsolved challenge & suffering faced by mankind for decades by one of the deadliest diseases with no proper cure i.e., "Cancer". Cancer can be cured if it is detected at the earliest, but many times this gets delayed as Pathologists should do the process manually going through each and every part of the histopathological images under microscope. Human error also becomes a factor & hence sometimes the report becomes falsely negative or falsely positive and treatment is delayed or started unnecessarily respectively.

To overcome all these, we are working on an algorithm that can supplement in identifying & segmenting cancerous nuclei & tumor buds. Hence helping early detection & begin treatment as soon as possible with maximum efficiency.

Index Terms - Histopathology, H&E, Nuclei, Augmentation, Segmentation, Mask.

I. INTRODUCTION

Human beings suffer from many diseases and cancer is one of the deadliest diseases which starts because of out-of-controlled growth of abnormal cells, most of them are initially identified because of the appearance of signs or symptoms or through screening. The traditional imaging techniques, based on radiation mechanisms such as X-ray, CT, MRI and Ultrasound, are non-invasive and have been widely used to study the structure of internal organs and to analyze the abnormalities, but none of these leads to a definitive diagnosis, which requires the examination of a tissue sample by a pathologist. So multiple pathologists come up with many different techniques which are quite complex, leading to many disadvantages.

Identifying and extracting the suitable features is an important stage of image analysis. Once the features are identified, the extraction of the same is the most challenging task as it depends on the accuracy with which the foreground region of interest is extracted. And in this project, we have designed an algorithm to segment the nuclei which can be used for identification and classification of the disease.

II. DATASET:

- We have downloaded the dataset from Kaggle i.e., the Breast Cancer Histopathological Images (known as breakhis dataset)
- The BreaKHis dataset contains microscopic biopsy images - benign and malignant breast cancer images which are of H&E stained (Hematoxylin & Eosin)
- The dataset is categorized as training and testing under which they are classified as benign and malignant.
- The images have a 400x optical zoom.
- Augmentation is a technique for boosting the model's efficiency by increasing the amount of training images.

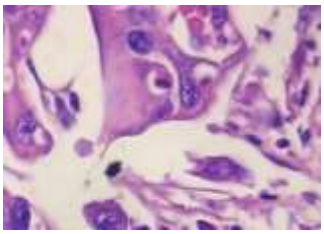

Fig 2.1: Malignant

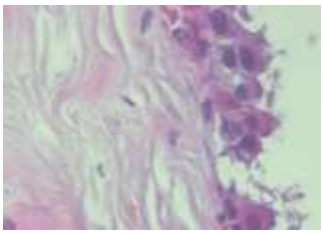

Fig 2.2: Benign

Masks:

- The masks are nothing but the ground truth used for training.
- We have obtained the masks from the Stardist pretrained model.
- The benign and malignant images from the dataset are given as input to the model and get their respective masks as the output.
- In this research, we used the following two types of masks to train our model:
    - Region mask: Using this, the model detects the outer lining of the nuclei.

- Boundary mask: Using this, the model segments the nuclei even from the occluded region.

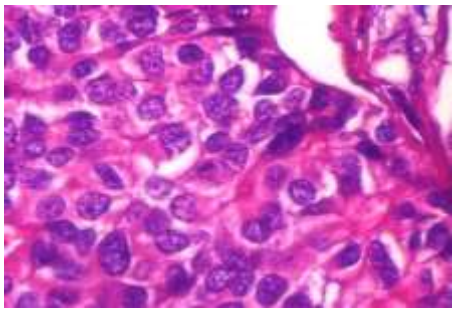

Fig 2.3: H&E-Stained Image

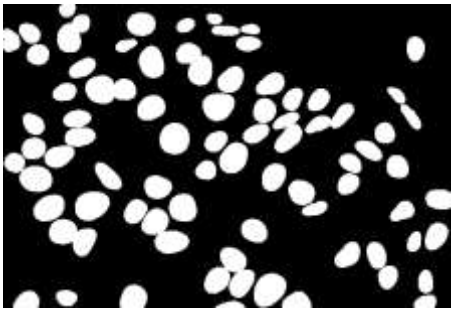

Fig 2.4: Region Mask

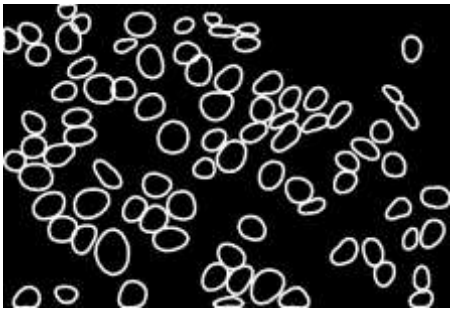

Fig 2.5: Boundary Mask

- Training the model with both region and border masks aids in the efficient identification of nuclei, which is a difficult process.

III. METHODOLOGY

The first stage starts with Image Acquisition i.e., taking a collection of digitized scanned images of Histopathology cells. These images have low noise when compared to scanned images.

The second stage is Object detection. The nucleus of cancerous cells is enlarged, irregularly shaped, highly coarse chromatin marginalized to the nuclei periphery and have visible nucleoli. These cancerous cell masses are identified by the deep learning model in this stage. Here two subtasks are performed to identify the cancerous cell they are Image classification and object localization where image classification involves assigning a class label to an image and object localization involves drawing a bounding box around one or more objects i.e., Histopathology cells in the image and finally the cancerous cell mass is detected using these subtasks.

The next stage is Image Segmentation using computer vision. The technique of segmenting a digital image into many portions is known as segmentation. Image segmentation is commonly used to discover and find items in photographs, as well as their borders. Image segmentation, more precisely, is the process of assigning a label to each pixel in an input cancer cell image so that pixels with the same label have certain features, such as the segment of images classified as cancerous nuclei and non-cancerous nuclei. Image segmentation produces a set of segments that cover the entire cancerous cell population. A region's pixels are similar in terms of some feature or calculated property, such as its shape, size, and texture. All image processing processes are aimed at improving object recognition, that is, finding relevant local features that can be separated from other objects and the background. The next step is to inspect each segmented pixel independently.

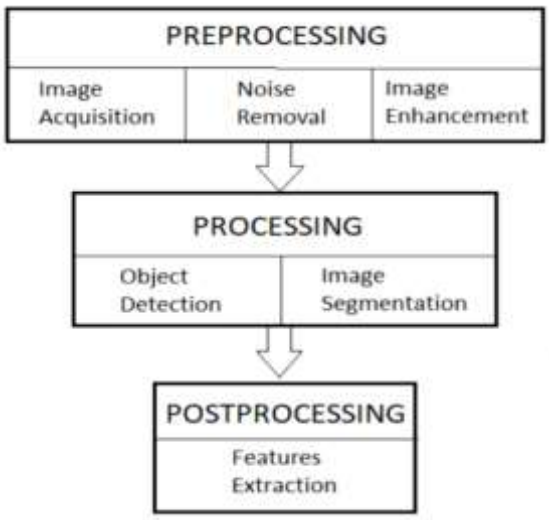

Fig 3.1: Methodology

The last stage is Post processing segmentation which is done using the Feature extraction method. The Image Feature Extraction stage is critical in our image processing research because it employs algorithms and strategies to recognize and extract certain desired areas or forms (features) of an image. Following segmentation, features from the segmented malignant cells region can be collected, and a diagnosis rule can be developed to accurately detect cancer nodules in that part.

CNN:

A convolutional neural network is a feed-forward neural network that is generally used to analyze visual images by processing data with grid-like topology. It's also known as a ConvNet. A convolutional neural network is used to detect and classify objects in an image. Yann LeCun, director of Facebook's AI Research Group, is the pioneer of convolutional neural networks.

A convolution neural network has multiple hidden layers that help in extracting information from an image. The four important layers in CNN are Convolution layer, ReLU layer, Pooling layer, Fully connected layer. The convolution layer has several filters that perform the convolution operation and in this layer every image is considered as a matrix of pixel values. ReLU stands for the rectified linear unit and here an element-wise operation is performed that sets all the negative pixels to 0 for feature maps extracted in the Convolution layer. In Pooling layer down sampling operation is performed that reduces the dimensionality of the feature map. The rectified feature map from the Relu layer goes through a pooling layer to generate a pooled feature map. The matrix from the Pooling layer is flattened and is fed as input to the fully connected layer to classify the image.

Different operations that are typically used in a Convolutional Neural Network (CNN) are Convolution operation, Max pooling operation, Need for up sampling, Transposed Convolution. The convolution operation is performed on the input data with the use of a filter to then produce a feature map. The function of max pooling is down sampling that is to reduce the size of the feature map so that we have fewer parameters in the network. Up-sampling is done since the expected output is a segmented image. Transposed convolution is exactly the opposite process of a normal convolution. It is a technique to perform up-sampling of an image with learnable parameters.

UNET:

UNet is a convolutional neural network architecture that's expanded with few changes in the CNN architecture. It was developed by Olaf Ronneberger et al. for Bio Medical Image Segmentation. It was invented to deal with biomedical images where the target is not only to classify whether there is an infection or not but also to identify the area of infection.

Network Architecture:

The architecture contains two paths. First path is the contraction path (also called as the encoder) which is used to capture the context in the image. The encoder is just a traditional stack of convolutional and max pooling layers. It consists of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. At each downsampling step we double the number of feature channels.

The second path is the symmetric expanding path (also called as the decoder) which is used to enable precise localization using transposed convolutions. Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution ("up-convolution") that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer a 1x1 convolution is used to map each 64- component feature vector to the desired number of classes. In total the network has 23 convolutional layers Thus it is an end-to-end fully convolutional network (FCN), i.e., it only contains Convolutional layers and does not contain any Dense layer because of which it can accept images of any size.

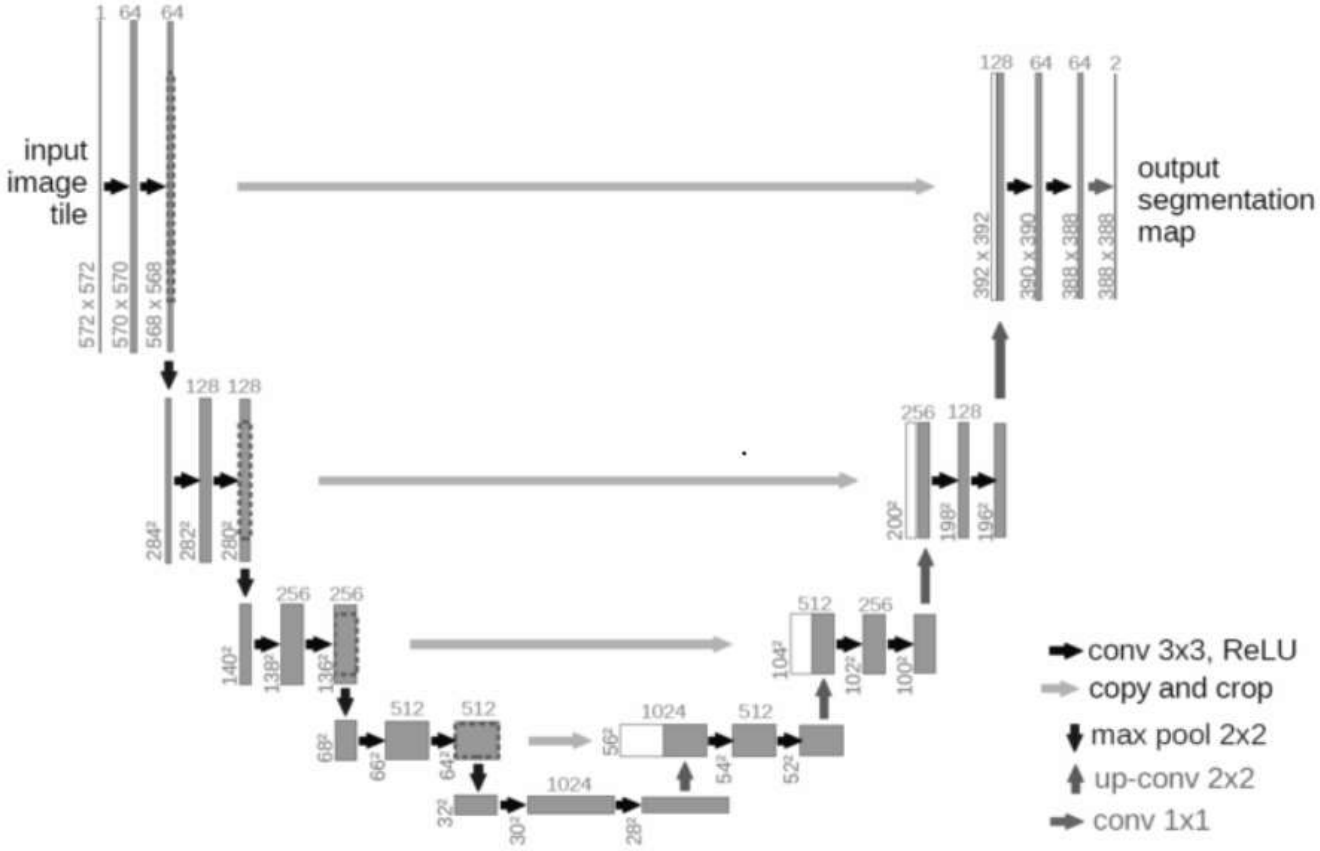

Fig 3.2: UNET Architecture

Measures used in Validation of the Model:

Measures such as Pixel Accuracy, Dice Coefficient, Jaccard Index are used to validate the model. Pixel Accuracy is the percent of pixels in your image that are classified correctly. Dice Coefficient is twice the Area of Overlap divided by the total number of pixels in both ground truth and predicted images. Jaccard Index is the area of overlap between the predicted segmentation and the ground truth divided by the area of union between the predicted segmentation and the ground truth.

IV. Experimentation and Result analysis

Training:

Training the model based on region masks:

1. First, we trained our model with the above-mentioned dataset whose results were not satisfactory even though it was predicting the output.
2. So, we used augmentation to increase the input images and region masks as ground truth which resulted in the improvement in the results by segmenting the nuclei with better efficiency and accuracy.

Training the model based on boundary masks:

1. We tried training the model using benign images, which was not able to predict the output properly
2. Then we tried with malignant images, which started giving better results since the number of images are more compared to that of the benign folder
3. As a next step, we augmented the dataset and first trained our model using benign images and then trained it using malignant images. As a result of both augmentation and the model, we came up with pretty good results; the model now segments the nuclei with great accuracy.

Validation:

We used multiple optimizers to train our model, such as Stochastic Gradient Descent, Adagrad, and Adam, which helped us train the model efficiently. And following are the metrics used in validating the model:

- Pixel Accuracy
- Dice Coefficient
- Jaccard Index

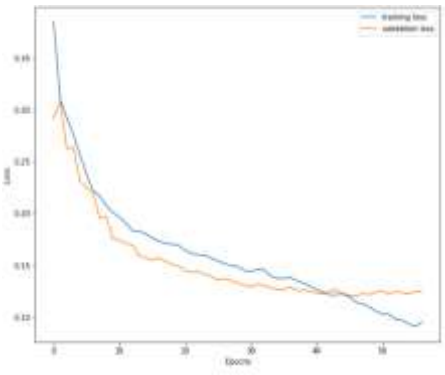

Fig 3.3: Pixel Accuracy

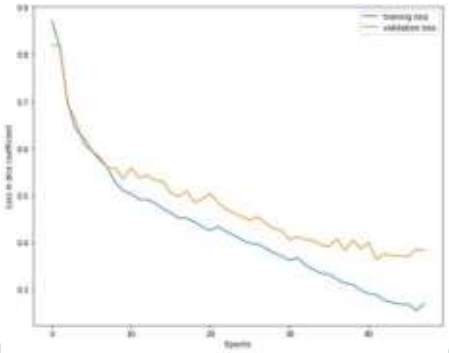

Fig 3.4: Dice Coefficient

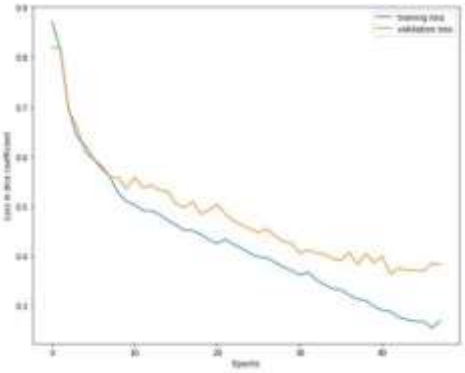

Fig 3.5: Jaccard Index

Testing:

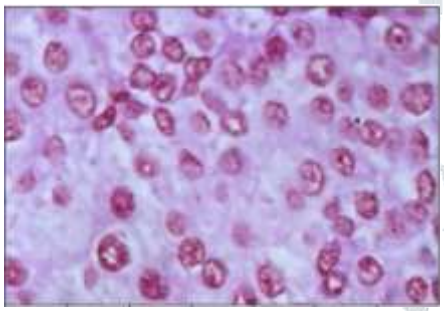

Fig 3.6: H&E-Stained Input

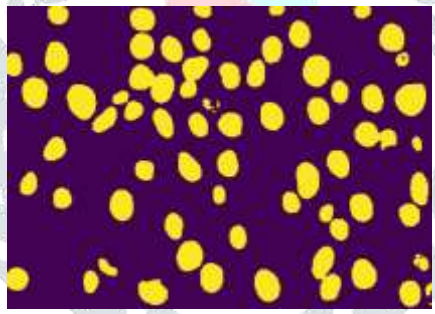

Fig 3.7: Region Mask Output

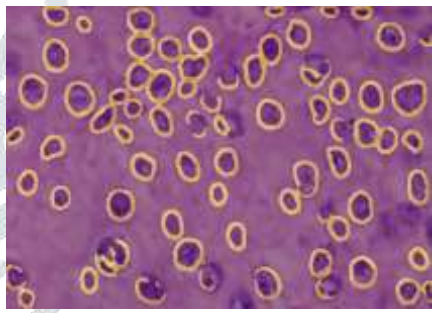

Fig 3.8: Boundary Mask output

V. Conclusion:

The proposed algorithm detects and segments the nuclei of an H&E-stained image efficiently when compared with the other techniques used. A novel approach of using U-Net as the architecture in an effective manner and the model is trained to segment the nuclei by creating region and boundary masks around it. This algorithm has simplified the work of a pathologist by detecting the cancerous cells even with occlusion and with minimal error and thus enables the treatment of the patient to be started early and saving lives of many.

VI. References

[1] A.D. Belsare and M. M. Mushrif - "Histopathological Image Analysis using Image Processing Techniques".
[2] Agne Paulauskaite-Taraseviciene, Kristina Sutiene, Justas Valotka - "Deep Learning-based Detection of Overlapping Cells".
[3] Ali IúÕna, Cem Direkoglub, Melike ùahc - "MRI Brain Image Segmentation using Deep Learning: Procedia Computer Science, Middle East Technical University".
[4] Cheng Lu, Muhammad Mahmood, Naresh Jha - "A Robust Automatic Nuclei Segmentation Technique for Quantitative Histopathological Image Analysis".
[5] Hui Kong, Kamel Belkacem-Boussaid, Metin Gurcan - "Cell nuclei segmentation for histopathological image analysis".
[6] J. C. Bezdek L. O. Hall L. P. Clarke "Review of MR Image Segmentation Techniques using Pattern Recognition: American Association of Physicists in Medicine."

[7] Jukka Iivarinen and Ari Visa - "Shape Recognition of Irregular Objects using Chain Code Histogram Contouring: Helsinki University of Technology".
[8] Metin N. Gurcan, Laura E. Boucheron, Anant Madabhushi, Nasir M. Rajpoot -"Histopathological Image Analysis".
[9] Nikhil. R. Pal and Sankar. K. Pal - "A Review of Image Segmentation Techniques: Indian Statistical Institute Kolkata".
[10] P M Shivamurthy; T N Nagabhushan; Vijaya Basavaraj - "A foreground marker based centroid initialized Geodesic active contours for histopathological image segmentation".
[11] P M Shivamurthy; T N Nagabhushan; Bhanu Prasad; Vijaya Basavaraj - "A foreground marker based centroid initialized Geodesic active contours for histopathological image segmentation".
[12] P M Shivamurthy; T N Nagabhushan; Vijaya Basavaraj - "An integrated DWT-wiener and marker controlled watershed driven active contours for nuclear segmentation in Histopathological Images."
[13] P M Shivamurthy; T N Nagabhushan; Vijaya Basavaraj - "A Curvature-Norm Based Centroid Initialized Distance Regularized Level Sets for Nuclear Segmentation in Histopathological Images".
[14] Salah Alheejawi, Mrinal Mandal, Hongming Xu, Cheng Lu, Richard Berendt, Naresh Jihad - "Deep learning-based histopathological image analysis for automated detection and staging of melanoma".
[15] Xiaofan Zhang, Fuyong Xing, Hai Su, Lin Yang, Shaoting Zhang - "High-throughput histopathological image analysis via robust cell segmentation and hashing".