BREAST CANCER STROMA CLASSIFICATION FROM HISTOLOGICAL IMAGES

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Abstract: Breast cancer is one of the major causes of death among women. Small clusters of micro calcifications appearing as collection of white spots on mammograms show an early warning of breast cancer. Early detection performed on X-ray mammography is the key to improve breast cancer diagnosis. In order to increase radiologist's diagnostic performance, several computer-aided diagnosis (CAD) schemes have been developed to improve the detection of primary identification of this disease. The rationale behind personalized cancer therapy is that patients respond to treatment differently depending on many factors such as stage of disease, cancer grade, immune response, and their genetic profile. The goal is to avoid needless and/or harmful continuation of an ineffective treatment, and to transform cancer therapy early on during a course of treatment by predicting who will effectively respond to a particular treatment. In this paper, an attempt is made to develop an Morphological operation algorithm for breast image segmentation for the detection of micro calcifications and also a computer based decision system for early detection of breast cancer.

Keywords— Breast Cancer, Histopahology, Image Classification, Stroma Maturity.

I. INTRODUCTION

The histopathological evaluation of a biopsy or surgical specimen is considered the gold standard for breast cancer diagnosis, enabling malignancy to be confirmed, the nature of the tumour established and the distribution and extent of the disease determined. Tumour grade is based on the degree of differentiation of the tumour tissue and can be applied to all types of cancer. It is a composite, semi-quantitative score of tubule formation, nuclear pleomorphism /atypia and mitotic activity in the malignant epithelium [1]. Stromal regions can be characterised according to their maturity. For certain types of cancers, as the tumor develops its microenvironment undergoes dynamic changes, such as increased production of fibrous tissue (desmoplasia) with abundant fibroblasts, which results in what is defined as immature stroma. Other cancers do not induce a desmoplastic reaction [2].The presence of immature stroma surrounding the tubular structures is a useful feature to confirm malignancy. Another particular case where pathologists might assess the stromal component is when determining the type of cancer. For example, lobular cancers do not normally present with a stromal reaction [3] .

They classified stromal tissue into three categories: mature, intermediate and immature. Their analysis of stromal regions from a dataset of 862 patients found that five- and ten year survival rates were poorest in the group with immature stroma and best in those with mature stroma. These are also characteristics of immature stroma. They suggested that this reactive stroma is a common feature and an intrinsic property of some tumours [4], [5].There has been a continuous search to find better image-based biomarkers that are indicative of disease and can be used to predict patient outcome or stratify patients with breast cancer [6]. With recent advances in digital histopathology, quantitative analysis of haematoxylin and eosin (H&E) images is now feasible. These include the application of statistical (gray-level co-occurrence matrix, local binary patterns), structural, model-based and transform-based methods (Fourier, Gabor, Difference-of-Gaussians and wavelet transforms) for extracting textural image features.
In recent years, there has been a growing interest in the changes that occur in the tumour microenvironment, in particular in the stroma, and their relationship to cancer progression.Beck *et al.* [7] found that the best histological predictors of patient survival were not from the carcinoma itself, but from the adjacent stromal tissue.

To the best of the authors' knowledge, this is the first study that attempts to categorize and automatically classify stromal regions in clinically acquired H&E stained slides. This will enable examination of the hypothesis that stromal maturity is related to growth and metastatic potential of tumours, and thus can be used for prognosis. These stromal features could also aid in the interpretation of the radiological signal and in particular relating the radiological features to microscopic changes. Variations in the stroma may cause detectable changes in water mobility (diffusion MRI [8]) and mechanical properties (Shear-Wave Elastography [9]). This, in turn, could enhance the ability of non-invasive pre-operative imaging to predict prognosis and also treatment outcomes (e.g. response to primary chemotherapy). we proposed an algorithm based on a support vector machine (SVM) classifier applied to a set of quantitative texture features to automatically classify stromal regions from images of H&E sections according to their maturity. Derivative-of-Gaussians (DtG) have been used for many applications, such as edge detection, retinal blood vessels extraction or texture analysis [10]–[12].

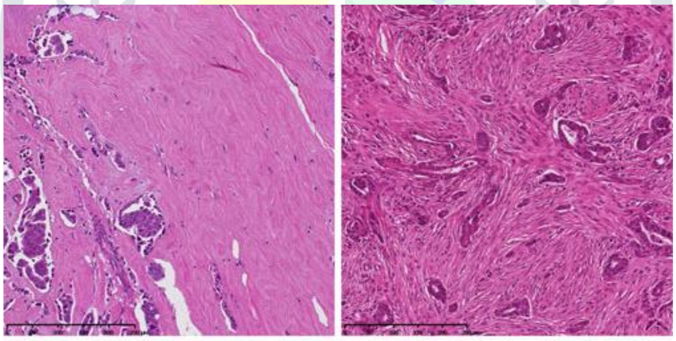
In this paper, we demonstrate the use of multi-scale Basic Image Features (BIF) and Local Binary Patterns (LBP) in combination with random decision trees classifier can be used for classification of breast cancer stroma. The computation of BIFs involves classifying the output obtained from convolution of an image with a bank of DtG filters into one of seven categories. These categories correspond to distinct local image structures, as defined by local symmetries [13]. BIFs have been shown to out-perform alternative methods when applied to standard textures [14] and applied to the segmentation of phase contrast microscopy (PCM) images of embryonic stem cells [15] and as a measure to characterise mammographic features according to their orientation with respect to the nipple [16].

II. CRITERIA FOR HISTOLOGICAL CHARACTERISATION OF BREAST CANCER STROMA

Two representative examples of (a) mature and (b) Immature stroma. Breast cancer stroma was classified as mature when composed of highly organised fine, elongated collagen fibres, normally following the same orientation with elongated, flattened nuclei of fibro cytes wrapped into its multiple layers. Stroma was classified as immature when consisting of randomly oriented fibres surrounded by a high concentration of fibroblasts and exhibiting regions with oedema .The initial goal of this experiment was to classify distinctive stromal regions that present the features explained above. Thus, areas comprising high levels of inflammatory cells were excluded from this experiment.

III. METHODS

SVM Classifier used to segment the cancer detected portion. To segment the portion, first have to filter out the acquired image based upon the asking methodology. The Morphological function including dilation and erosion method will be applied extracted throughout the filtered image. By the method of morphological bounding box will be drawn over the affected portion. Then, the region enclosed by bounding box will be splitted out separately with the SVM Classifier. Finally, we compare all classification technique and graphical representation of tumour region is plotted.



(a) (b)

fig 1. example images of (a) mature and (b) immature stroma tissue.

1) IMAGE ACQUISTION: Image acquisition is the creation of photographic images, such as of a physical scene or of the interior structure of an object. The term is often assumed to imply or include the processing, compression, storage, printing, and display of such images. Image acquisition can be defined as the action of retrieving an image from some source. Acquire the input images from MRI scan images. These scan images are collected from the internet.

2) COLOR CONVERSION: The input images will be converted into grayscale images**.**The converted gray scale images may lose constrast, sharpness, shadow and Structure of the color image.Each pixel is a single sample representing only an amount of light that is it carries only intensity information. The RGB Color model is an additive color model in which Red, Green and Blue light are added together in various ways to reproduce abroad array of colors.

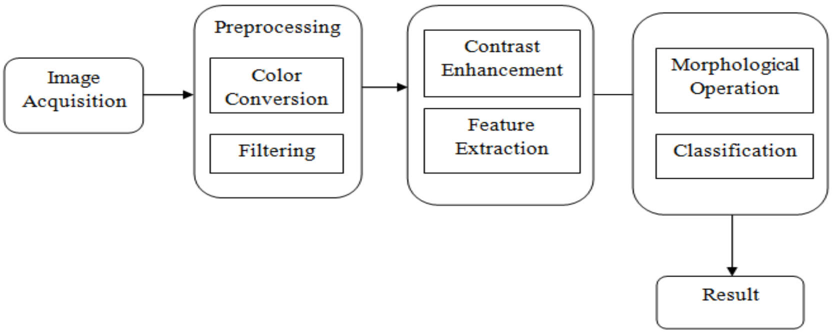


fig 2: architecture diagram

3) FILTERING: Preprocessing include the input MRI breast tumor image and image filtering. In image filtering, several different filters can be used but the magnetic resonance image (MRI) image does not contain a lot of noise.In Signal Processing, a filter is a device or process that removes some unwanted features or Components from a signal.In image processing filters are mainly used to suppress either the high frequency in the image that is smoothing the image or the low frequencies.

3.1) MEDIAN FILTERING: The median filter is a non linear digital filtering technique, often used to remove noise from an image or signal.Median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserves edges.

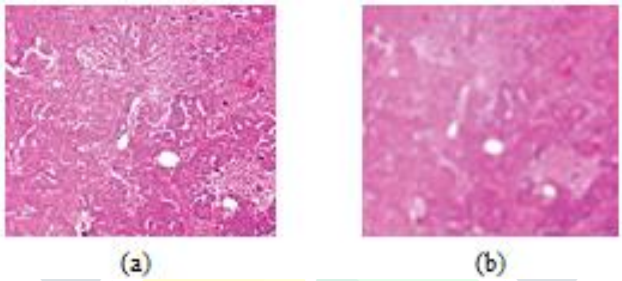


fig 3(a).original images 3(b).filtered images

4) CONTRAST ENHANCEMENT: Poor contrast is one of the defects found in acquired image. The effect of that defect has great impact on the contrast of image. When contrast is poor the contrast enhancement method plays an important role. In this case the gray level of each pixel is scaled to improve the contrast. Contrast enhancements improve the visualization of the MRI images. Contrast enhancement technique is used for enhance the MRI image.Constrast is the difference in visual properties that makes an object distinguishable from other objects and the background.contrast is determined by the difference in the color and brightness of the object with other objects.

5) FEATURE EXTRACTION: Feature extraction is a method to search the related features from picture, which are used to understand the picture easily. This input data group picture is transformed into compressed form is called feature extraction. It can reduce the work for further processing such as picture classification. Here the GLCM and LBP feature extraction method is used. GLCM and LBP is used after the contrast enhancement. Feature extraction involves reducing the amount of resources required to describe a large set of data. Feature extraction is a method of constructing combination of the variables to get around these problems while still describing the data with sufficient accuracy.

6) MORPHOLOGICAL OPERATIONS: After changing over the image in the binary format, some morphological operations are applied on it. The motivation behind the morphological operator is to discrete the tumor part of the image. Now just the tumor segment of the image is visible, which is shown with White color. Tumor region has the highest intensity than the other regions of the image. Morphological operators are applied after the contrast enhancement..Morphological is a broad set of image processing operation that process images based an shapes.Morphological operations apply a structuring images to an input image, creating an output image of the same size. The erosion and dilation methods are used for morphological operation.Dilation adds pixels to the boundaries of objects in an image,while erosion removes pixels on object boundaries.

7) CLASSIFICATION: Support vector machine are surprised Learning models with associated learning algorithms that analyze data used for classification and regression analysis. One of the best known methods for pattern classification and image classification is SVM. A set of training images is separated by SVM into two different classes. Optimal separating hyper plans based on kernel function are build by SVM. Class -1 belongs to images which feature vector are placed on one side of hyper plane and others are in class +1.

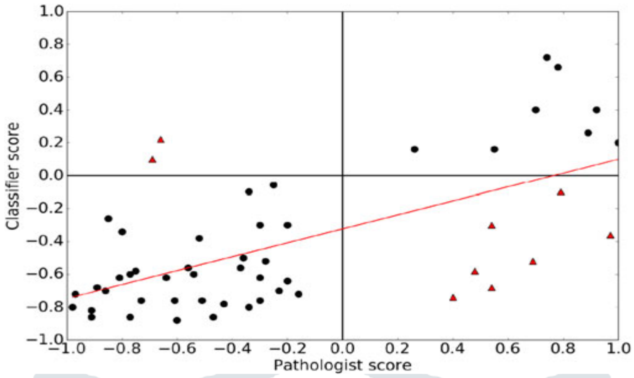


fig 4.comparison between the classifier output and observer continuous score.

IV.CONCLUSION

This study has demonstrated the ability of a Median filtering and the combination of Morphological operation and LBP to determine the maturity of breast stroma as represented in H&E stained slides. Inclusion of the light line DtG prefiltering significantly improved the discrimination of the method over direct application of the LBP method the grey-scale luminance images. This work demonstrates that texture based classification of H&E images from IBC could have practical clinical applications in distinguishing stromal morphology. Although stroma assessment is not currently a standard procedure for pathologists when performing a diagnosis or in prognostication, the idea of using this component as a prospective feature for evaluating tumour growth, aggressiveness and disease progression is gaining ground.

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