

Breast Cancer Detection using RF Images- A Machine Learning Approach

Deekshitha.S.P¹, Nagananandini.G²

P.G. Student, Department of CS&E, Acharya Institute of Technology, Soldevanahalli, Bengaluru, India¹

P.G. Student, Department of CS&E, Acharya Institute of Technology, Soldevanahalli, Bengaluru, India²

ABSTRACT: At the early stage the cancer detection was identified using computer aided system and was tested on the locally with locally advanced breast cancer (LABC) patients. But later the proposed system was integrated with multi-parametric quantitative ultrasound (QUS) spectroscopic methods in conjunction with advanced machine learning techniques. Specifically, a kernel-based metric named maximum mean discrepancy (MMD), a technique for learning from imbalanced data based on random under-sampling, and supervised learning were investigated with response-monitoring data from LABC patients. The CAT system was tested on 55 patients using statistical significance tests and leave-one-subject-out classification techniques. Textural features using state-of-the-art local binary patterns (LBP), and gray-scale intensity features were extracted from the spectral parametric maps in the proposed CAT system.

KEYWORDS: Support Vector Machine , CAT Systems, QUS techniques, RF images, Image processing, Segmentation.

I. INTRODUCTION

According to data from the World Health Organization, breast cancer is one of the most prevalent cancers, accounting for 29% of all cancer cases worldwide. In spite of recent advances in the early detection of breast cancer, it still is often not be discovered until it is fairly large or locally advanced. Locally advanced breast cancer (LABC) includes breast tumours greater than 5 cm in diameter, which are often at an advanced stage locally and inoperable, but have not yet spread outside the breast and/or regional lymph nodes. Women with LABC are often recommended "up-front" chemotherapy before their surgery (neo-adjuvant chemotherapy) in order to shrink the tumour, a technique which was pioneered in the setting of LABC.

An early detection of patient response to chemotherapy is potentially crucial in such cases in order to avoid continuation of an ineffective treatment and increase survival rates. Assessing the efficacy of cancer treatments on subjects in clinical applications is typically conducted late during treatment. This is mainly because monitoring cancer therapy effects is currently performed at macroscopic levels, which relies on clinical practice to measure the size of a tumour. Although this approach is well established for research, clinical screening, and treatment planning, changes in size can take weeks to months after the completion of treatment to become apparent, and do not always occur even when the treatment is effective due to scar tissue formation. To overcome this problem, cancer response monitoring at microscopic level has recently been suggested.

This can be done with recent advances in medical imaging and by the understanding that cancer therapy-induced cell death can be detected early after the start of treatment, non-invasively, through different functional imaging modalities. These include functional methods which probe changes in cell structure associated with tumour cell death or tumour vasculature. Currently, the most established methods for cell death detection are those focussed on the detection of apoptosis (programmed cell death). These methods could potentially be used in a clinical setting and are based on imaging modalities such as positron emission tomography (PET), single photon emission computed tomography (SPECT), and magnetic resonance imaging (MRI). However, these methods have two main limitations: they are presently expensive, and require contrast agents to be administered in order to enhance the contrast from soft tissue. The potential for side effects from allergic reactions and the radioactivity of some agents are also limiting

factors. The different methods based on quantitative ultrasound (QUS) provide cost-effective, non-invasive, and a rapid framework to assess cancer therapy effects.

These methods alleviate the requirement for injecting external contrast agents as the alteration in bio-acoustic properties of tissue with cell death is the source of change in imaging contrast. In other words, programmed cell death causes many morphological changes in tumour cells including nuclear condensation and fragmentation, cell swelling, and chromatin dissolution, which have been demonstrated to directly or indirectly affect ultrasound backscatter characteristics of tumour. For example, chromatin changes due to cell death have two effects on ultrasound backscatter intensity. Initial nuclear condensation and fragmentation with cell death increases ultrasound backscatter intensity. Nuclear changes increase the degree of compactness and the randomness of fairly regular backscatter distributions of micro-echoes, which can produce a large backscatter signal. However, in late cell death, when a large fraction of the nuclear scatters is lost (advanced necrosis), the amplitude of the backscattered signal can be reduced. Quantitative ultrasound has a main advantage over conventional ultrasound imaging in that it uses metrics that are predominantly independent of instrument settings. Such quantitative measures are derived by analyzing the radiofrequency (RF) raw data before forming B-mode images, i.e., before detecting its envelope and log amplification, and describe bio-acoustic characteristics of the scanned tissue. QUS methods often involve spectrum analysis (spectroscopy) of the backscatter RF signals over regions of interest, forming parametric maps.

II. PROBLEM STATEMENT

Accurate classification of malignant and benign breast cancer tissues were done using many techniques but classification using CAT systems gave a very accurate predictions. Kernel Based methods on QUS using RF images were used for response of patient monitoring applications..

III. DATA FLOW

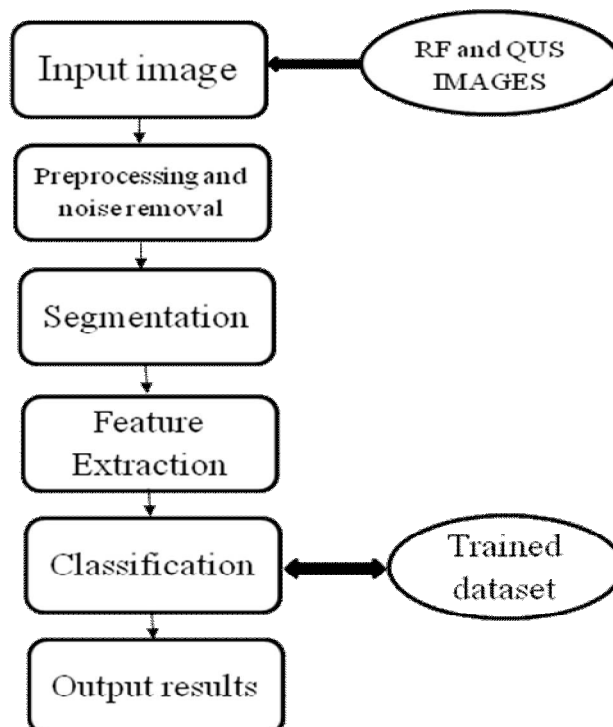


Fig. 3.1

IV. IMPLEMENTATION DETAILS

5.2 Stages

Implementation of the Project contains the following stages which classifies the extracted images as benign and malignant using classifiers .

1. Image Acquisition
2. Preprocessing
3. Segmentation
4. Feature Extraction
5. Classification

5.3 Stage Description

5.3.1 Image Acquisition:

- The first stage of any vision system is the image acquisition stage.
- The image has been obtained by Gallery.

5.3.2. Preprocessing:

The objective of the preprocessing phase is to apply possible image enhancement techniques to obtain the required visual quality of the image.

Preprocessing has two steps-

1. Grayscale Image
2. ROI Extraction
3. Smoothed Image
4. Histogram Equalization Image

5.3.2.1. Grayscale Image:

The cancer image is in RGB type which is an additive color of red, green, and blue. The image is converted into gray scale image for further processing.

5.3.2.2. ROI Extraction:

In this stage, infected region are cropped using ROI extraction.

5.3.2.3. Smoothing Image:

After ROI extracted process, smoothed image is obtained. In image processing, a **Gaussian blur** (also known as Gaussian smoothing) is the result of blurring an image by a Gaussian function. The most commonly used software graphics system to decrease the noisy data in the image.

5.3.2.4. Adaptive Histogram Equalization:

The contrast enhancement of the image can be observed by applying adaptive histogram equalization (enhance contrast using Adaptive Histogram Equalization). The histogram equalization techniques are adopted to enhance the quality of the X ray mammogram image. It eliminates the background information, redundant and hidden details to process in a fast and easy manner. It also deals with enhancing the contrast of suspicious areas in the mammogram image. It is used to increase the contrast of the image without affecting the information structure.

V. RESULTS

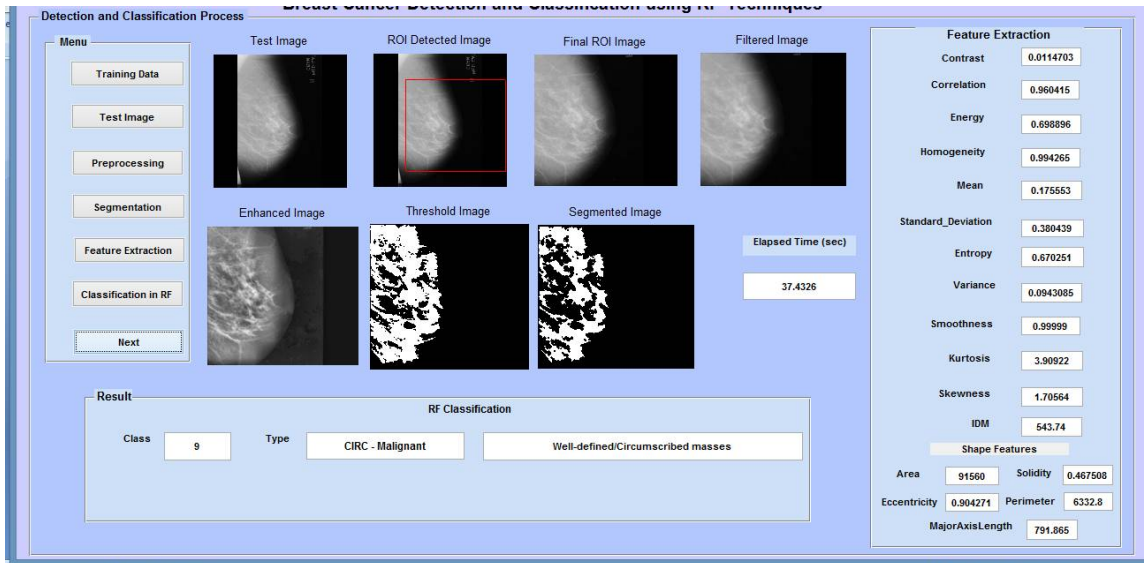


Fig. 6.1

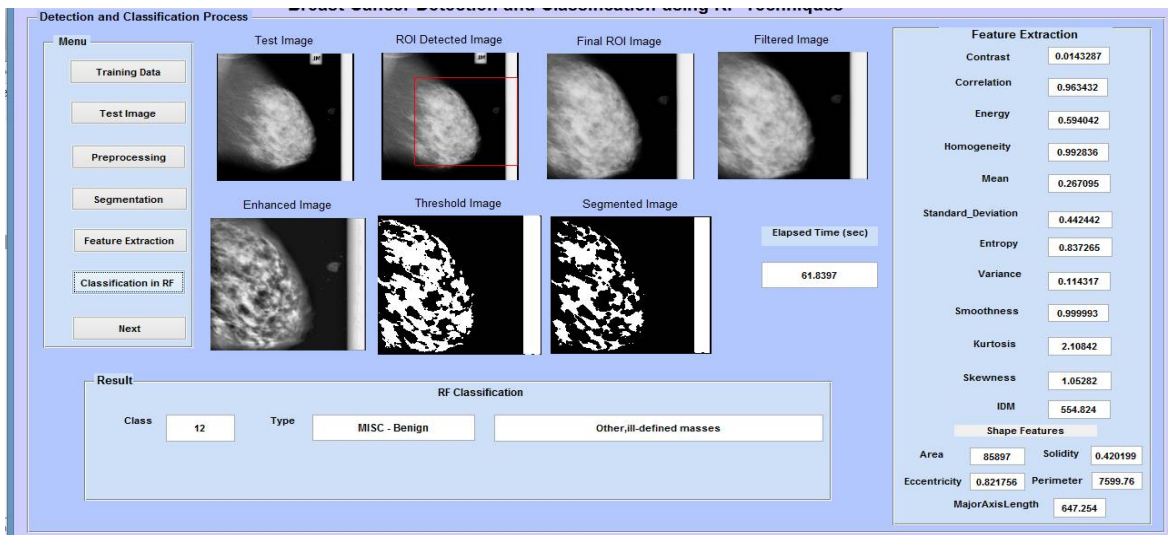


Fig. 6.2

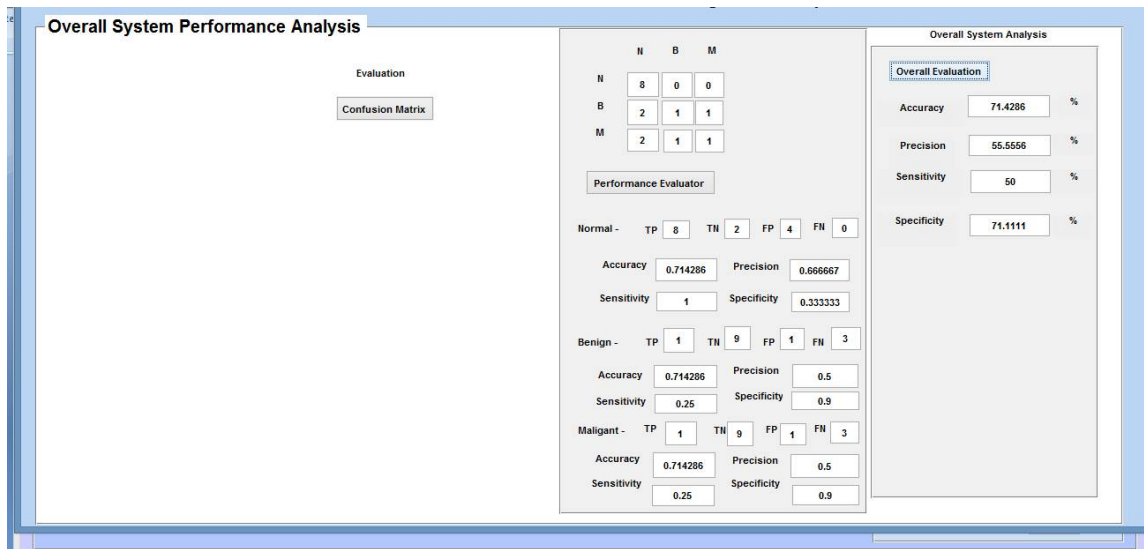


Fig. 6.3

REFERENCES

- [1] J. S. Ross, "Cancer biomarkers, companion diagnostics and personalized oncology," *Biomarkers Med.*, vol. 5, no. 3, pp. 277–279, 2016.
- [2] E. C. Hayden, "Personalized cancer therapy gets closer," *Nature*, vol.458, no. 7235, pp. 131–132, 2015.
- [3] K. Sikora, "Personalized cancer therapy," *Personalized Med.*, vol. 2,no. 1, pp. 5–9, 2005.
- [4]I. I. Wistuba, J. G. Gelovani, J. J. Jacoby, S. E. Davis, and R. S. Herbst "Methodological and practical challenges for personalized cancer therapies,"*Nature Rev. Clin. Oncol.*, vol. 8, no. 3, pp. 135–141, 2014.
- [5] B. Stewart and C. P. Wild, *World Cancer Report 2014 Int. Agency Res.Cancer*, 2014.
- [6] O.L. Mangasarian, W.N. Street and W.H. Wolberg. Breast cancer diagnosis and prognosis via linear programming. *Operations Research*, 43(4), pages 570-577, July-August 1995.
- [7] <ftp://ftp.cs.wisc.edu/math-prog/cpo-dataset/machinelearn/cancer/>.
- [8] Ian H. Witten, Eibe Frank, *Data Mining-Practical Machine Learning Tools and Techniques with Java Implementations*. Morgan Kaufmann Publishers.
- [9] Eryi Zhu, Fanyuan Yang, *Chemometrics Techniques and Applications*, Beijing Scientific Publishers.
- [10] Matthias Otto, *Chemometrics: statistics and computer application in analytical chemistry / New York Weinheim Publishers*.
- [11] Mehmed Kantardzic, *Data Mining: Concepts, Models,Methods and Algorithms*, Wiley Interscience.