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Fatty tissues in breast increases for breast cancer patient due to lockdown in COVID-19

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Abstract
Cancer causes cells in the body to change and grow out of control. It is one of the most dreaded diseases of modern world although multidisciplinary scientific investigations are making best efforts to combat this disease. Breast cancer begins in breast tissue, which is made up of glands for milk production, called lobules and ducts that connect lobules to the nipple. Normally, breast cancer develops from cells lining the milk ducts and slowly grows into a lump or a tumour. Breast cancer may be invasive or non-invasive. Invasive cancer spreads from the milk duct or lobule to other tissues in the breast, whereas, non-invasive ones lack the ability to invade other breast tissues. Non-invasive breast cancer is called “in situ” and may remain inactive for entire lifetime. Women with breast cancer need to get precautions during COVID-19. Specially, for the fatty tissue tumor increase for those who have already detected breast cancer. This paper studied the increase of masses in breast cancer patient during the lockdown period. It is due to mental anxiety of patients.

Keywords: COVID-19, breast cancer, mammogram images and invasive cancer

Introduction

Breast is referred as mammary gland in scientific term. With reference to the Merriam-Webster dictionary the Breast is either of the pair of mammary glands extending from the front of the chest in pubescent and adult females of humans and some other mammals. It is also either of the analogous but rudimentary organs of the male chest especially when enlarged [1].

The different technologies which are used to view the human body in order to diagnose, monitor or treat medical conditions are referred to as Medical Imaging. Specific technologies are used to investigate and analyze different information about the explicit area of the body being studied or treated, related to possible disease, injury or the helpful for medical treatment. There are several medical imaging technologies that are used nowadays like X-ray, Ultrasonography (USG), Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) etc. In breast cancer diagnosis several imaging technologies are used including Mammography, Ultrasonography and Magnetic Resonance Imaging. Several researches have shown that early detection with mammography saves lives and increases treatment options. One of the main advantages of mammography is the comparative cost effectiveness and availability [2].

The breast is the region that extends from lateral thoracic artery at the top to the infra-mammary fold at the bottom. The mammary gland has a small projection, the nipple, surrounded by a portion of pigmented skin called the mammary areola.

The breast is prone to various benign and malignant conditions. The most common benign conditions are puerperal mastitis, fibrocystic breast changes and mastalgia. The latter part is very serious in nature that is Breast Cancer. Breast cancer, a malignant tumour developed from breast cells is considered to be one of the major causes for the increase in mortality among women, especially in developed and developing countries. More specifically, breast cancer is The second most common type of cancer and the fifth most common cause of cancer-related death. So, it continues to be a significant public health problem in the world [3].

Most masses are benign, that is, they are not cancerous, do not grow uncontrollably or spread and are not life-threatening. Some breast cancers are called in situ because they are confined within the ducts (ductal carcinoma in situ) or lobules (lobular carcinoma in situ) of the breast. Nearly all cancers at this stage can be cured. Lobular carcinoma in situ (also known as lobular neoplasia) is an indicator of increased risk for developing invasive cancer in either breast [4, 6].

Breast cancer stages range from 0 to IV. The breast cancer diagnosis process is basically two folds. The screening process is simply used to find abnormalities in the breast. The conclusion reached through process of analyzing histopathological slide with present technologies and procedures like biopsy to determine whether a tumour is malignant or benign [7].

Digital mammography is a recent technique for recording x-ray images in digital code instead of on x-ray film, as with conventional mammography. Digital mammography has some advantages over conventional mammography due to use of computer. Radiologist can magnify or zoom images to see the actual place of abnormalities. Digital Mammography has been proved to be the most effective and reliable screening method for early breast cancer detection [8, 12].

Qualitative assessment is done using Accuracy Estimation measures that are evaluated through quantitative measures derived through the comparison of each segmented region “mask” with its corresponding “gold standard”. The gold standard is generated by manually segmenting the region from each mammogram. The boundary of the region is then manually traced using general purpose image processing software to extract the actual region, Ground Truth (GT), from mammogram image and verified by radiologist [13, 16].

Related Works

Over the past 20 years, continuous advancement in field of image processing algorithms, computer technology in terms of computational power and storage, and digital medical imaging technologies have allowed the development of powerful computer-assisted analytical tools towards diagnosis of critical diseases like cancer. Last few years, several state-of-the-art computer aided diagnosis (CAD) systems have been developed to deal with different fields of disease analysis [17]. The breast cancer diagnosis is one of the most well accepted implementations of CAD to assist the medical practitioners.

In identification process of disease, the initial process is to detect mass in breast followed by diagnosis for final conclusion. The digital mammographic imaging is the most trustworthy process for early detection of breast. Recent studies reveal that majority of clinical tests including digital mammography and biopsies performed are benign, resulting in wastage of valuable time of medical practitioners and at the same time increasing the possibility of false detection. The efficient CAD system can screen the benign cases and assist the experts in terms of qualitative and quantitative precision.

The widespread application of CAD can be found after the emergence of digital mammography in the early 1990's [18]. Recently, CAD has become a part of routine clinical detection of breast cancer on mammograms at many mass screening program and hospitals [19]. Now the recent introduction of slide digital scanners, histopathology biopsy slides can also be digitized and kept in digital image format. So, image processing algorithms can also be applied on histopathological biopsy slides to analyze the image for decisive inferences.

The common architecture of a CAD system for digital mammogram includes image preparation, pre-processing, features extraction and detection. The basic building blocks of those processes are image preparation including orientation, artefact removal and noise reduction, image registration, image enhancement, segmentation and detection. The process of segmentation is most important topic of CAD analysis. In mammographic image analysis, segmentation is related with the pectoral muscle suppression, edge detection, determination of Region of Interest (ROI), anatomical segmentation, segmentation of abnormalities like mass and micro-calcification.

The incidences of artefact on mammographic images are typical problem. Artefacts are in the form of identification labels, markers and wedges in the unexposed air-background (non-breast) region. Pre-processing can be defined as the basic operations on the medical images towards extraction and detection of desired features by CAD. The primary operation of pre- processing includes image registration, enhancement, pectoral muscle suppression, edge detection, ROI (region of interest) extraction by determining the contour. As discussed earlier pectoral muscle suppression, edge detection, ROI (region of interest) extraction are part of segmentation process.

Researchers reviewed several well accepted mammogram image registration techniques and classified them according to their functionality [20]. According to the survey a spatial mapping between two images is defined as image registration. The primary objective of registration is to align one image to another by finding the optimal transformation or mapping function. It involves a searching plan to enhance a similarity measure. This similarity measure is determined using certain characteristics of the images. Feature space, transformation, similarity measure and search strategy constitute a typical registration framework [21] automated image processing systems like CAD. Broadly, the enhancement of mammogram is performed by intensity and contrast manipulation, noise reduction, background removal, edge sharpening, filtering etc.

Mammogram segmentation is to extract breast ROIs containing all anatomical regions including the suspicious mass or micro-calcification. The aim of segmentation of suspicious regions is to extract the location and classify the apprehension into benign or malignant [22]. The abnormal area of a mass has almost undeviating intensity, higher than the surrounding and a regular shape with various size and fuzzy boundaries [23]. Scientists have used different segmentation methods or their combinations to segment the mammogram image accurately. Commonly applied segmentation schemes are region growing, edge detection, wavelet, statistical methods, mathematical morphology, the fractal model, Fuzzy methods to segment a ROI in digital mammograms.

The feature extraction and decision making is the final step of CAD. The image registration followed by enhancement and segmentation processes improve the image quality and separate the different areas. Now it is easier to extract the desired features and draw a conclusion by decision making systems. The features to be extracted from the mammogram image is different types of abnormal mass or masses, micro-calcification along with different morphological and anatomical properties related to cancer detection. The extracted feature can be categorized into three different sections namely intensity features, shape features and texture features. Some researchers suggested the recommendations for feature extraction and selection of important features: discrimination, reliability, independence and optimality [24].

Most of the feature extraction methods used the intensity values whereas very few applied the spatial dependency between them. Feature selection is one of the most challenging tasks in CAD because it leads to diagnosis phase. The reduction of the feature set is usually achieved either by converting the features into a new-space and creating new features as the combinations of the original ones or to maximize an objective function by choosing a subset of the features [25]. In feature choice, a subset of features can be extracted either using comprehensive search or consecutive search algorithm. The best probable subset is determined by a comprehensive search technique.

Data Set

Dataset is a collection of similar and related data stored for processing. Further this can be defined as a collection of data that contains individual data units organized in a specific format. A data set generally contains a collection of many types of data. Medical dataset can be defined as a collection of pieces of information, especially those that are part of a collection to be used in an analysis of a problem, such as the diagnosis of diseases. Dataset is used the Mammographic Image Analysis Society (MIAS) dataset [26, 27].

MIAS dataset is sufficiently large to conduct experimental analysis. Moreover, the dataset contains 322 mammogram images of different size, shape and morphology. The images are also classified and benchmarked by an expert team of radiologist of MIAS into three distinct categories based on their parenchymal density. Further, the radiologist has provided all relevant information regarding any abnormality present. The images are classified into normal, asymmetry, presence of mass, calcification etc. The mass is further classified according to the type of mass present, like, well-defined/circumscribed masses, spiculated masses, ill-defined masses etc. The choice of MIAS database for conducting most of the experiments described in this paper is due to its sufficiently large volume, image quality, easy availability and diverse benchmarked cases. MIAS dataset have been used to prove the efficiency of the proposed methods, quantitative assessment and to compare the results with other important dissertations.

Related Works

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The purpose of image enhancement is to increase the interpretability or perception of information in images. Enhanced image provides improved input for automated image processing systems like CAD. Broadly, the enhancement of mammogram is performed by intensity and contrast manipulation, noise reduction, background removal, edge sharpening, filtering etc. Mammogram segmentation is to extract breast ROIs containing all anatomical regions including the suspicious mass or micro-calcification.

The feature extraction and decision making is the final step of CAD. The image registration followed by enhancement and segmentation processes improve the image quality and separate the different areas.

Cancer causes cells in the body to change and grow out of control. Cancer cells form a mass called a tumour. Types of cancer are named after the parts of the body where the tumour originates. Breast cancer begins in breast tissue. It is made up of glands for milk production. These glands are called lobules and ducts that connect lobules to the nipple. Breast cancer is the second most common type of cancer and the fifth most common cause of cancer-related death. So, it is a significant public health problem in the world for female. There are some rare cases of breast cancer in male also.

Normally, breast cancer develops from cells lining the milk ducts and slowly grows into a lump or a tumour. A malignant tumour has the ability to spread beyond the breast to other parts of the body via the lymphatics or the blood stream. Breast cancer may be invasive or non-invasive. Invasive cancer spreads from the milk duct or lobule to other tissues in the breast, whereas, non-invasive ones lack the ability to invade other breast tissues. Non-invasive breast cancer is called “in situ” and may remain inactive for entire lifetime. Early diagnosis is the most effective way for treatment to reduce mortality. Breast cancer affecting the women is known to cause high mortality unless detected in time. The mortality incidence ratio is much higher in developing countries than in developed countries.

Breast tumour can be malignant or benign. It will be able to track the development of the tumour over time. This work is a result of series of discussions with the medical practitioners.

Analysis of the proposed method includes determination of quantitative, qualitative, comparative and complexity measures. The proposed method has been rigorously tested over dataset for prediction of breast cancer. The primary goal of this work is to devise method that will assist radiologist, pathologist, oncologist and physicians for predicting breast cancer.

Analysis of algorithms is incomplete if Complexity Analysis is not performed. It assesses the efficiency of the proposed method. However, such comparative study should be done with other research work with the proposed method. It is discussed in the Performance Measure Metrics.

A critical review of existing methods was undertaken to establish the progress of knowledge and state of the art research happening in the globe. A Max-Mean and Least-Variance method was used for breast tumour detection [28]. The limitation of the method is not to handle a large number of breast images for accurate cancer detection. An Artificial Neural Network was implemented for breast cancer detection with the extracted features [29]. Since the proposed neural network is composed of three different layers for detection so it failed to minimize the detection time. A weighted K-means support vector machine (wKM-SVM) was introduced for prediction of breast cancer. The weighting scheme does not have the high accuracy in breast cancer prediction [30]. It is about 70 % and the proposed method in this has an accuracy about 97%.

CNN wavelet and curve let transform were presented for breast cancer detection [31]. The accurate detection of breast cancer was less than 75%. An ensemble empirical mode decomposition is proposed to discover breast cancer using ultra-wideband (UWB) microwave images the accuracy of the method is 70% [32]. A selective ensemble method KNN, SVM, and Naive Bayes detected the breast cancer using both ultrasound images and mammography images [33]. This ensemble method failed to identify specify features in the breast for detection of cancer. A mass detection technique was introduced to attain less false positive rate in the breast cancer detection with high sensitivity [34]. The technique does not reduce the detection time. A CNN-based approach was developed to classify the histological breast cancer images with the extracted features [35, 36]. The approach does not use whole-slide breast histology images.

Methods based on automated and semi-automated methods were developed to detect abnormal masses. Researchers use density-weighted contrast enhancement algorithm using adaptive filtering and edge detection [37]. An adaptive multilayer topographic regional growth algorithm was developed for detection of masses [38]. A grey-level–based iterative and linear segmentation algorithm, a dynamic programming approach, dynamic contour modelling etc. were developed to segment mass lesions from surrounding breast tissue [39]. The important feature in automated mass detection and classification is to detect mass boundary [40].

In this paper the exact process of prediction is made using Gradient Boosting ensemble method. The method achieves result with an accuracy of 97.34%. The result is higher than the exiting methods. It indicates positive point for prediction of breast cancer.

Proposed Method

The interesting of the paper is to identify abnormal mass in digital mammogram. The masses i.e. tissues which are absent in normal breast anatomy is called abnormal masses. The size and shape of density of masses are variable in nature. So it has a unique impression in the mammogram image. In this paper, method is proposed to extract the related features and identify the abnormal masses from digital mammogram. It is the role of medical practitioners to draw a conclusion about the nature of abnormalities. Image processing techniques have been developed to help radiologists for diagnosing breast cancer. Studies proves that an early diagnosis of breast cancer is always increase the survival rate. Anatomical segmentation of Breast Region of Interest (ROI) is used to detect abnormal masses and also isolates normal and abnormal regions in the breast tissue and also able to isolate different types of abnormalities, if present.

Digital Mammograms initially requires pre-processing to improve the quality of the image. Detection of abnormalities is based on the images obtained after segmentation. Anatomical Segmentation of Breast ROI determines abnormalities in breast. It not only segregated the regions but also removes all unwanted dots, edges and discrete objects from the edge map.

Segmentation process is made on the edge map to differentiate various regions on the breast based on their intensity values. Actually, each region has a different intensity value. Different intensity values of fatty tissues, glands, lobules and the ducts are segregated into different regions. Mass, tumours or calcifications present within the breast has distinctly higher intensity values than the normal tissues of the breast. All the closed structures on basis of their intensity values are categorized. Pixels intensities are also varied within each segmented region but the majority of the pixels have similar intensity values. The arithmetic Mode value is calculated for each region from the original mammogram and replaces those pixels in the region with the computed mode values. Figure 1 shows the result after operation of the method.

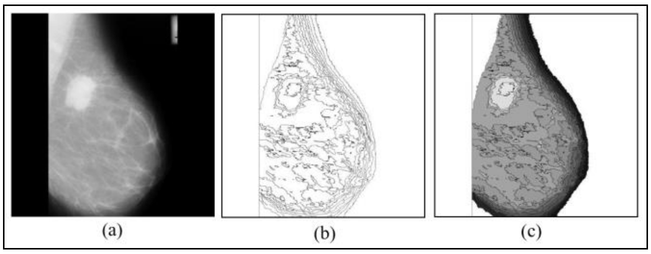

Fig 1: (a) Original Mammogram, (b) Anatomical Regions and (c) Mammogram with mass

The scanning process starts from the first row of the image and proceeds to row major order up to last row. As soon as region with higher intensity is found, coloring process started for the region by first comparing the pixel intensity at the level up to the pixel of original mammogram image. Four boundaries of each pixel located north, east, west and south are checked to find out whether they are colored or they form the boundary pixel. If the pixels are not colored as well as not boundary pixels then further searching is made. A stack is used to store the seeds, calculated from intensity value, for investigation. while a List is used to store The pixels, already traversed of the regions, are stored in list. All the pixel positions within the List are compared with the original image pixel. It then stored their intensity values for calculating the Mode value. The pixel locations of each region are replaced by the computed Mode value intensity. The proposed method enumerated each region along with their respective statistical mode value. This dataset is used for further statistical analysis. First, the Arithmetic mean for the distribution is calculated to obtain the deviations of each region. Subsequently the Standard Deviation of the dataset is calculated. Now the mean value is calculated along with the standard deviation using the dataset. Now, the regions are categorised into four discrete levels according to their colour intensity. The method highlighted the abnormal regions by Red colour and suspected region with Blue colour. The other regions are also coloured with different shades according to the different categories. The result is shown in figure 2.

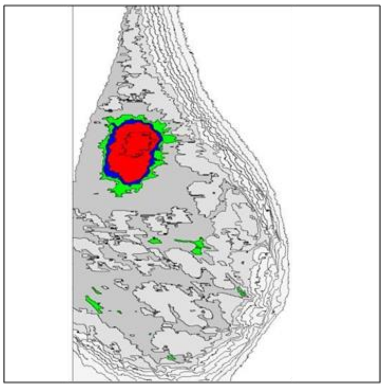

Fig 2: Highlighted Regions with Abnormal Masses Marked Red Color in Mammogram Image

Results obtained by applying the proposed algorithms on MIAS image comprised of predominantly Fatty tissue where no abnormalities are present. This image represents the control image for experiment indicating no mass is detected as shown in figure 3 and mass detected in fatty tissue in figure 4 due to mental anxiety of breast cancer affected patient.

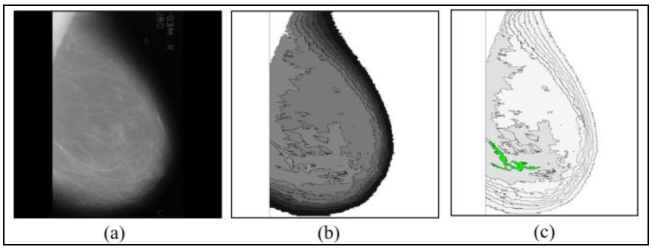

Fig 3: (a) Original Mammogram, (b) Anatomical Regions after applying proposed method (c) Mammogram showing Absence of Abnormal Region(s)

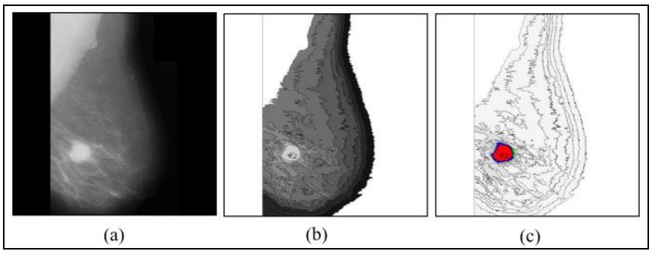

Fig 4: (a) Original Mammogram, (b) Anatomical Regions for fatty tissue and (c) Mammogram showing Abnormal Region (s)

Results obtained by the proposed algorithms on MIAS image comprised predominantly Fatty Fibro-Glandular tissues where circumscribed masses are present as abnormalities. It is shown in figure 5.

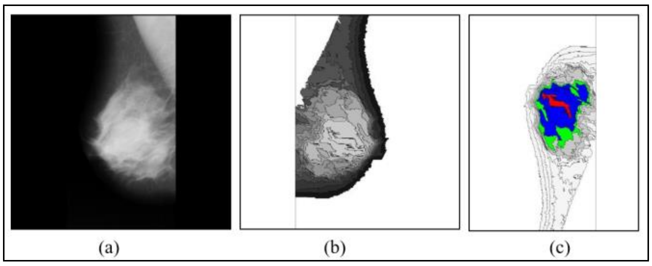

Fig 5: (a) Original Mammogram, b) Anatomical Regions and c) Mammogram showing presence of abnormal region

Results obtained by applying the proposed algorithms on MIAS image comprised predominantly Dense Fibro-Glandular tissues where Spiculated masses are present as abnormalities as shown in figure 6.

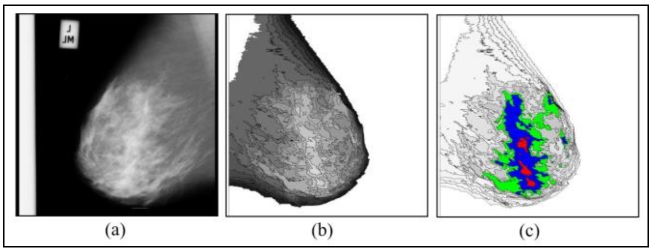

Fig 6: (a) Original Mammogram, b) Anatomical Regions after SRGA and c) Mammogram showing presence of abnormal regions

Conclusions

A sequence of distinct method has been proposed. The results for the dataset shows excellent detection of abnormalities in mammogram. The accurate mass detection was achieved by the proposed method. Results of the proposed method shows a reliable detection rate of tumour, if present, within the mammogram. For identification of mass, Accuracy value 96%, Sensitivity 97.6% and Specificity 88.6% is achieved. Whereas, accuracy estimation for boundary of mass show Accuracy value 99.9%, Sensitivity 96% and Specificity 95.2%.

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