

Identification of Defects in the Mammographic Images Based On Graphical Approach

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ABSTRACT: Breast cancer has become a great threat to the women kind. The spreading of cancer is generally due to the abnormal proliferation of cancer cells. Microcalcification clusters are the main cause of cancer and it has become the primary sign of breast cancer. It is not easy to determine the type of cancer cells only by detecting the presence of microcalcification clusters. A novel method using multiscale morphology was proposed to classify the microcalcification clusters using mammograms based on their connectivity. This method concentrates only on the tumour cells rather than the tissues where the tumour is present. It also concentrates on individual tumour cells than concentrating as clusters as a whole. Thus a connectivity is established within the clusters for the individual microcalcification. Based on different scales the microcalcification graphs are generated to denote the structure and topology of microcalcification clusters. The topological feature space for classifying the microcalcification clusters are extracted from the graph theoretical features. Microcalcification clusters are classified based on k – nearest neighbors-based classifiers. The methods validity is evaluated using MIAS, DDSM and fullfield digital dataset.. The tumor state in the mammograms were identified based on different classifiers like FNN, FRNN, KNN and SVM classifiers. The overall performance of the process is measured based on Accuracy, Sensitivity and Specificity.

KEYWORDS: Microcalcification, cluster, abnormal proliferation, tumour cells.

I. INTRODUCTION

Decomposition of an image at progressively lower resolutions is practically attractive because of the compatibility it provides across the range of envisioned transmission schemes, from Super HDTV to NTSC. With increasing resolution, the disparity (in pixels) between corresponding points increases. In a well composed stereo image, the vertical disparity can be made zero; nevertheless, even an exhaustive one-dimensional search in the maximum fusible horizontal disparity range would become a computationally formidable task at higher resolutions. Hence from a computational standpoint also, a hierarchical scheme that estimates on a coarse-to-fine scale is preferable. The multiresolution theory of Mallat, unifies the concepts of subband coding and wavelet theory and also provides a psychophysical justification for operating at different scales. The wavelet decomposition of images provides an efficient way of representing information in an image, and the decomposed subimages can be quantized and coded very efficiently. The context (significant objects in the scene) of the image is visible at all resolution levels; these progressively lower resolution images form a pyramid structure that can be used for the hierarchical block disparity estimation. The quantized and reconstructed image retains most of the edge information crucial for stereo perception. On the other hand, transform based compression methods that achieve compression by smoothing the image do not preserve the sharpness of the edges. Also, the subband coding method does not suffer from 'tiling' at low bit rates, which is a serious drawback in transform based methods that operate on blocks. A multiresolution based hierarchical disparity estimation scheme is considered here. The wavelet decomposition of an image can be achieved using the equivalent filtering approach. Figure.1.a shows a three level decomposition. The separable 2D filtering approach is used wherein the filtering is done

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along the rows and then along the columns. Daubechies' compactly supported orthonormal filters have been used to reduce the filtering complexity. It has been observed that there is no appreciable improvement in using filter orders above six. Hence DAUB6 filters have been used for all the images in our experiments. The orthonormality of the filters permit downsampling by a factor of two, after filtering. Thus this decomposition preserves the total number of pixels after decomposition, unlike the Laplacian pyramid structure which results in a one-third increase in the number of pixels. At each level there are four subimages that are one-fourth the size of the image at the level below. The subimage obtained by lowpass filtering in both directions is called the coarse image; typically, it carries most of the energy present in the original image and has an intensity distribution similar to that of the original image. The other three subimages are called the detail images, because they contain the high frequency details in either the horizontal or vertical direction or both. Only the coarse image at each level is subjected to further decomposition to obtain the next level subimages. The detail images have an almost Laplacian intensity distribution i.e, there are more pixels with intensities close to zero and only a few pixels with significantly high absolute intensities. Hence these detail images can be either scalar or vector quantized efficiently at very low bits per pixel (bpp) without any visually displeasing artifacts. The bit allocation for the detail image pixels increases at higher decomposition levels, due to the higher fraction of total energy usually contained in these levels. Compression ratios as high as 1:100 have been reported using entropy constrained lattice vector quantization of the detail images.

Some disparities in health and health services can be attributed to "social factors" such as the higher likelihood of being uninsured for Blacks and Latinos, transportation in inner cities or over representation of minorities in Medicaid health plans with restrictive payment policies. Empirical research has found disparities, however, even when these social factors are ruled out by controls or by design. In some "experiments" in which insurance, access, and other factors do not vary, black patients are treated differently than white patients. In other words, disparities may arise from the interaction between doctor and patient. In this paper, we are concerned with disparities from this second source, the clinical encounter. In particular, we focus on disparities that originate in the physician's behavior, including any demand-side reaction to that behavior. One view of the origin of these disparities is that health care providers are simply prejudiced against members of minority groups and treat these patients with lower regard than Whites. Another commonly mentioned hypothesis is that providers hold preconceptions about patients that are conditioned on group membership. Doctors' "stereotypes" that minority patients are less likely to comply with treatment, for example, might generate disparities. Finally, in an earlier paper, we show how the presence of greater uncertainty in interpreting symptoms of disease for minority patients can itself be a source of disparate treatment, even among fair-minded providers. All three of these explanations are a form of what social psychologists label "group categorization," that is, acting toward a person based in part on their membership in a social group like race or ethnicity. In the sections that follow, we study doctors' group-based decisions of the following form: being less willing to interact with members of the minority group (prejudice), interpreting a symptom of illness as a less reliable indicator of severity for a minority patient or holding differential beliefs about the group's underlying severity (clinical uncertainty), and holding a belief that minority patients are less likely to comply with treatment recommendations (stereotyping). In conducting this analysis we rely heavily on the labor economics literature—the field of economics where issues related to discrimination have been treated most extensively. Within a unified framework, we link our analysis to policy and show that policies to address disparities will work differently depending on which mechanism is responsible. We consider information-based policies to reduce uncertainty or to break stereotypical patterns. We also consider enforcing "rule-based" policies that require, for example, that Blacks be treated the same as Whites. All policies have costs of implementation, of course, but in our discussion of policies, we focus on the potential benefits of information and rule-based approaches. Information-based policies, though ineffective when information is not the underlying problem, at least satisfy the medical creed, "first, do no harm." Rule-based policies run a greater risk of unintended consequences. Enforcing parity in treatment across racial groups without dealing with information problems that might be generating the disparities in the first place can degrade the value of health care for all social groups—a lose-lose proposition. One conclusion of our analysis is that social policy to reduce disparities arising from the clinical encounter should be based on evidence that differentiates among the possible routes of cause. The power of the discriminatory practices analyzed in this paper, and the role and scope of policies suggested to combat them, depend greatly on how market forces interact with such practices in the long-run. In the labor literature, acknowledged that competitive market forces would eliminate the differential wages across groups predicted by his taste discrimination theory. At the end of each section we study the long-run equilibria of the model presented and address its completeness, by questioning the determination of the key parameters in a health care context. For this purpose, we rely also on analogies to the labor literature. Before

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we analyze disparities stemming from the clinical encounter, we first define a standard or benchmark of clinical decision-making that is both fair and efficient.

II. DATA

The data constituting of three datasets were used which contains image patches for different cases. First dataset was extracted from MIAS which contains 20 image patches of 512 x 512 pixels. Second dataset from DDSM which contains 300 image patches. Mammograms were acquired using Hologic Selenia mammography unit. Binary images such as 0's and 1's were used where 0 is normal and 1 is the microcalcification which can be detected manually

III. METHODOLOGY AND WORKDONE

The mammography input images with micro-calcifications were taken as input. Based on the particular threshold the micro calcification locations were identified. The connectivity between the identified micro calcifications were estimated based on the dilation operation. The dilation operation is employed for three times to the input image. While applying dilation each time the connectivity between the different micro-calcifications were identified and they were represented in a graphical format. The features were extracted based on the parameters of the graphs like Number Of Sub graphs, Average Vertex Degree, Maximum Vertex Degree, Eccentricity value, Average Vertex Eccentricity, Diameter, Average Clustering Coefficient, Giant Connected Component Ratio, Percentage Of Isolated Points. In addition to the statistical features texture based features were extracted based on Local binary pattern algorithm. The classification of the features were done based on Fuzzy Nearest Neighbor, Vaguely Quantified Nearest Neighbour, Fuzzy Rough Nearest Neighbour, K Nearest Neighbour and SVM classifier. The performance of the process is measured based on accuracy, sensitivity and specificity. Methodology includes [1] Identification of microcalcification, [2] graph creation, [3] feature extraction, [4] classification and [5] performance measures.

$$\text{Specificity} = \frac{TN}{FP+TN}; \text{ACC} = \frac{(TP+TN)}{(FP+TN)+(TP+FN)}; \text{Sensitivity} = \frac{TP}{(TP+FN)}$$

Where, TP is True Positive

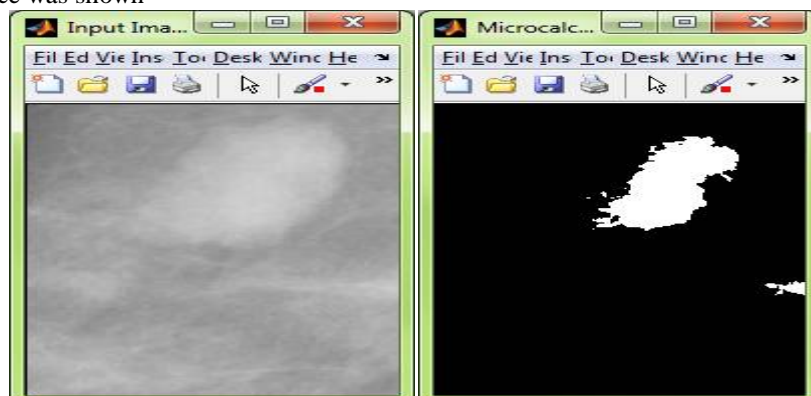
TN is True Negative

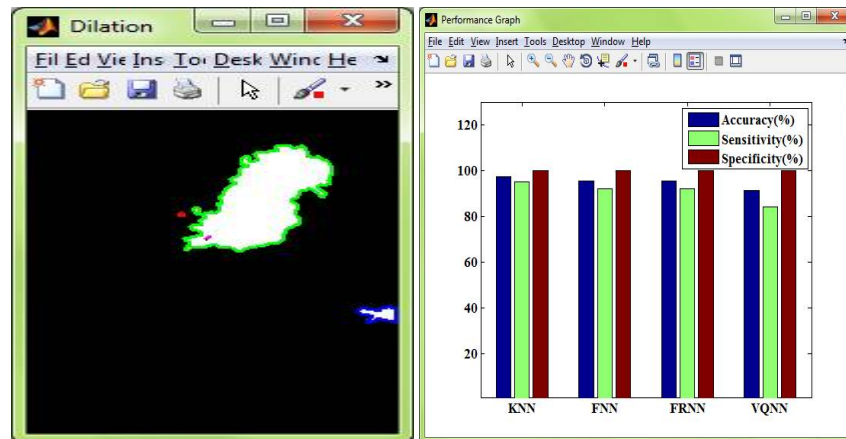
FP is False Positive

FN is False Negative

IV. EXPERIMENTAL RESULTS

We have implemented an automatic Experimental Results and discussion: To discriminate between the benign and malignant tumours and to evaluate the performance two digitized datasets and one full field datasets were used. For manual annotations the MIAS dataset provided CA of about 96% and for automatic detections the CA was 95%. Best results are provided by the digital datasets which provided more accurate detection when digital mammography was used. The second best dataset was provided by the MIAS dataset which showed that both the manual and automatic annotations showed the same performance. Using LOOCV very similar results were shown using DDSM and a decreased performance was shown





[3] Dilation

[4] Performance Graph

VI. CONCLUSION

From the input image micro-calcifications were extracted from the images based on the thresholding operation. Dilation operation were employed in three stages and in each stage the graph based model in the images. The features were extracted from the images based on the graph parameters. Texture features were extracted from the images based on Local Binary pattern .The extracted features were then classified based on different classifiers. SVM classifier is used in additional inorder to classify the images. The performance of the process is measured based on the performance metrics. The values of the Accuracy, Sensitivity and Specificity, were compared with existing methods.

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