Identification of Cancer on Digital mammogram using Univariate Classification Technique

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Abstract:-Breast cancer is a leading cause of death among all cancer for women in the age between 35 to 55. Digital mammogram is one of the technique to find the cancer at a earlier stage these are many methods to defeat and diagnosis Breast Cancer such as biopsy, clinical exams and self examination .In this paper we proposed the technique which is called by the name univariate classification scheme (equal distance method) is used to cluster the image from that high density pixels to be identified to detect the stage of cancer In the field of medical application using latest technology such as data mining to increase the efficiency to the best treatment of women community.

Key words: Classification, Clustering, Digital mammogram, Univariate Classification

I. INTRODUCTION

The modern world affects the life time of the human in different ways. The science and technology innovation affects the life style in both fields like advancement and the defect. Computer process is one among the invention to bring the revolution in the modern knowledge era. Computing and knowledge processing applications improves the living condition in the many areas and many ways. Medical science is one among the potential domain where computing process is used for the enhancement of human lifestyle. Many research processes are carried out in the integration of computing and the medical application is for the betterment of the human health. Most of the medical application which is used with the computations is aided to the practitioners to take the decision on their drug recommendations and the identification of the diseases [3]. The computing technologies are well developed , as well as the medical science also using the technology but they determine suitable ways to adopt the technology and the processing depends on the requirement of the medical applications are challenging task to the researchers.

The computation process is used in the Medical science field by experts as a tool, but the tools are developed by the computer experts with various technical procedures. The technical experts derive the concept and integrate the same in various medical science applications.[4] The Medical field computational process is used for data and images analysis[8]. The research process involves analysis, design of solution and implement the identified existing algorithms in medical science .This analysis process involves to adopt the latest technology such as data mining[16,18,5,6]. The data mining process involves various techniques such as data cubic representation, classification, clustering and decision support system [19,11,22,13]. This research deals with the determination of cancer stage using medical image analysis using univariant analysis.

II PROPOSED ALGORITHM

A. *Data collection*

The images are collected from the cancer institute laboratory and then 18 image properties are applied on original image. It consists of 12 color images and 6 gray scale images. Image properties includes ascending red16,descending red16, red16, region16, mirror, magnify, minify, Spectrum, bwlog, bwparabolic, designer16, -90, +90 and so on. The following figure shows original image of the patient Amul. The size of this image is 1012 X688 pixels.

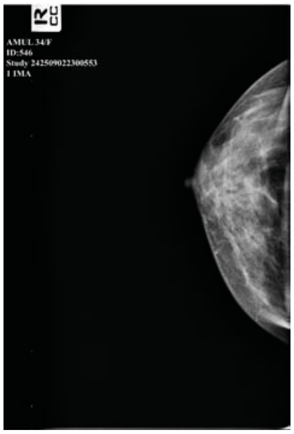


Fig 1:Amul1 Original image

B.Pre processing

Pre-processing includes cropping which is used to cut the black parts of the image and written labels. It removes the unwanted parts of the image to improve the appearance such as the change of aspect ratio. This operation is done using image editing software such as Adobe Photoshop. It is a pixel based image editor, which is used for editing, animating and authoring. The original

image contains 1012 X688 pixels. After cropping, the size of the image is 260 pixels width and 555 pixels height. Horizontal Resolution is 300 dpi. Vertical Resolution is 555 dpi.Bit depth is 24.The frame count is 1.

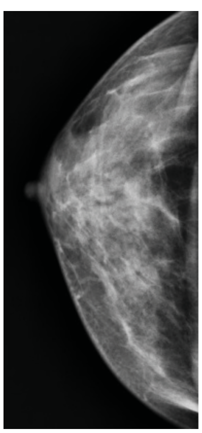


Fig 2: Preprocessed image of Amul1

The colour representation is RGB. Syngo fastview is a software, which is a standalone viewing tool for DICOM images. It is used to generate ascending red16,Auxctq16 ,BWlnVLog16, BW Parabolic16, correction16,Cyclic16 ,Descending red16, Design16,.Grayscale16 ,Hot body16, Hot metal16, Iso count16, Heart16, Rainbow16 , Red16, Spectrum, Parathyroid16, Warm metal 16 , Mirror +90 , Mirror _90 , +90,-90 , magnify + and Magnify – attributed images for the clustering process.

The image is swept vertically and horizontally to make all images in same size. To sweep the image vertically cut 2.2x4.7 inches. To sweep the image horizontally cut 4.7x2.2 inches using the software Adobe Photoshop. The size of the image is DPI of the output device (i.e) 300 dpi. After cropping the size of the image is .87x1.85 inches. Good quality 300 dpi pre-processed images are used for clustering process using mat lab 7.0 software. There are 4 images for each patient. Each image is clustered into 5 clustered sub images. Apply 18 properties for each image. Finally 1080 image for each patient. For 4 patients totally more than 4000 images are analyzed for the research work .

C.Methodology

The research methods are starting from the mammographic image and proceeds with the determination and verification of stage of cancer. The collected digital mammogram image is processed and converts the pixel value into corresponding Digital Numbers or Index Values. The digital Mammogram values are classified according to the Univariate using multi view analysis. According to clustering and classification process, the density level of digital Mammogram area is identified.

The clustering analyses are implemented with direct image and rotational conversion method. In the direct method the image is processed with ascending red16,Auxctq16, BWlnVLog16, BW Parabolic16, correction16,Cyclic16 ,Descending red16, Design16,.Grayscale16 ,Hot body16, Hot metal16, Isocount16, Heart16, Rainbow16 , Red16, Spectrum, Parathyroid16, Warm metal 16 attributes. 16 represents for the bit process and the attribute represented for the pre processed image. In the rotational property Mirror +90 , Mirror _90 , +90,-90 , magnify + and Magnify – properties.

After processing all the above methods , the average and frequency of the image stage is considered to determine the stage level .The identified area index value and its property are represented for stage level calculation using average method. The grade and stage of cancer is processed and the prevention possibilities could be recommended from the practitioners.

D.Univariate classification

Univariate classification is the first method of the research work. It explore untransformed or transformed datasets to analyze (classify and re-classify) image data and display continuous field data. In the majority of cases these procedures perform classification which is purely based on the input dataset, without reference to separate external evaluation criteria.

In almost all instances the objects to be classified are regarded as discrete, distinct items that can only reside in one class at a time. Separate schemes exist for classifying objects that have uncertain class membership and/or unclear boundaries or which require classification on the basis of multiple attributes called equal interval values. Typically the attributes used in classification have numerical values that are real or integer type. In most instances these numeric values represent interval or ratio-scaled variables. The table provides details of a number of univariate classification schemes together with comments on their use. A useful variant of the method, known as hybrid equal interval, in which the inter-quartile range is itself divided into equal intervals, and does not appear to be implemented in mainstream.

Selected univariate classification schemes

Classification scheme	**Description/application**
Unique values	Each value is treated separately, for example mapped as a distinct color
Manual classification	The analyst specifies the boundaries between classes required as a list, or specifies a lower bound and interval or lower and upper bound plus number of intervals required
Equal interval, Slice	The attribute values are divided into *n* classes with each interval having the same width=Range/*n*. For raster maps this operation is often called *slice*
Defined interval	A variant of manual and equal interval, in which the user defines each of the intervals required
Exponential interval	Intervals are selected so that the *number* of observations in each successive interval increases (or decreases) exponentially
Equal count or quartile	Intervals are selected so that the number of *observations* in each interval is the same. If each interval contains 25% of the observations the result is known as a quartile classification. Ideally the procedure should indicate the exact numbers assigned to each class, since they will rarely be exactly equal

The equal interval method, attribute values are divided into *n* classes with each interval having the same width=Range/*n*. This method aids to determine the range value of the available attribute values. The classification is not accurate due to the multi variable classification of the Image.

In this work, the range values are determined according to number of cluster. Let us assume the number of cluster is 5. The interval is calculated according to unique values method. Therefore the color combination 0-255 is dived into 5 with roundup ranges. The interval is 256/5 = 51.

The range values are

Range number	Starting	End
1	0	50
2	51	102
3	103	154
4	155	206
5	207	255

The classification is done with individual layer and combinational layer values. In the individual layer, only one layer values are considered for the classification of the selected layer and the remaining values are extended. According the affected area, clustered image is adopted. Affected image is classified into 5 clustered images from 0 to4 using the following procedure.

E.Clustring procedure

The image is converted into digital number system

1. The image is divided into 3 layers such as R,G,B.
2. Image reversing is done to find the minimum and maximum value of each layer
3. Find the maximum and minimum of value of each layer.
4. Find the difference between maximum and minimum values of each layer.
5. The classification standard 5 is adopted based on the medical standardization process of mammography analyses especially for breast cancer affected particle detection which gives equal interval for each layer. The image is split into five equal intervals. Each interval is having minimum and maximum values.
6. The layered range difference are tabulated based on the affected particles of maximum and minimum value.
7. In the original image, pixel values are presented between the minimum and maximum value of each layer in each intervals. If it is presented between each interval then construct the clustered image.
8. The step 7 and 8 is repeated until to construct 5 clustered images.

F. Average value of classified image

1. Calculate the total no of pixels in each image.
2. Identify the non-zero element combination of set value to determine the percentile of affected particle in particular layer
3. Calculate the sum in correspond to non-zero elements which is occurred in the segments sub image for each and every layer using the counter.
4. After the calculation of non zero elements and their sum of each and every layer
    a. Find percentage of red pixel. The total number of pixel is 144300.
    b. The percentage of red pixel Using the formula %red = nze in red layer/total no. of pixel.
5. Find the pixel density value using the formula pixel density=Sum/nze
6. From the percentage of red pixel density and single pixel density, find the affected density in the red layer

   Affected density in Red layer= Red pixel density/%Red. The same procedure is repeated for the remaining two layers.
7. After finding the affected density in all layers find average density of three layers.
8. For each image, there are 5 clustered images from 0,1,2,3,4,5.
9. The same procedure is repeated for all the clustered images.

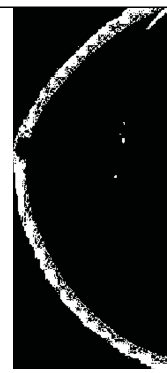
III EXPERIMENT AND RESULT

The following tables,table1 shows non zero elements and sum values. Table 2 shows affected density of pixels**.**

Table1: Non zeo elements and their DN values

	Name of the Image		Affected Density in Red	Affected Density in Green	Affected Density in Blue	Average

File name	amutha1_ascendingred16	Cluster1(Img0)	Cluster2(Img1)
Range		0-50	51-102
Total Pixel	555 x 260	144300	144300
NZE in Layer 1		61160	53511
NZE in Layer 2		61160	53511
NZE in Layer 3		61160	53511
Sum of NZE in Layer 1		1000359	3998265
Sum of NZE in Layer 2		10736296	6471460
Sum of NZE in Layer 3		11284515	5753103
			
File name	Cluster3(Img2)	Cluster4(Img3)	Cluster5(Img4)
Range	103-154	155-206	207-255
Total Pixel	144300	144300	144300
NZE in Layer 1	13251	5284	11094
NZE in Layer 2	13251	5284	11094
NZE in Layer 3	13251	5284	11094
Sum of NZE in Layer 1	1680980	939852	2815591
Sum of NZE in Layer 2	1529576	557581	2200748
Sum of NZE in Layer 3	1336785	488587	2325627

1	amutha1_ascendingred16	Cluster 0	0.38591	4.14176	4.35326	2.96031
		Cluster 1	2.01489	3.26123	2.89922	2.72511
		Cluster 2	13.81439	12.57014	10.98577	12.45677
		Cluster 3	48.57359	28.81699	25.25123	34.21394
		Cluster 4	33.01107	25.80241	27.26654	28.69334
2	amutha1_auxctq16	Cluster 0	0.09102	1.02600	1.62827	0.91510
		Cluster 1	56.13572	68.48030	97.02200	73.87934
		Cluster 2	58.31804	29.47723	62.28375	50.02634
		Cluster 3	59.06940	16.57323	39.16669	38.26977
		Cluster 4	5.91317	0.78335	3.62693	3.44115
3	amutha1_bwlnvlog16	Cluster 0	0.70344	0.70344	0.70344	0.70344
		Cluster 1	31.78129	31.78129	31.78129	31.78129
		Cluster 2	6.69831	6.69831	6.69831	6.69831
		Cluster 3	6.91404	6.91404	6.91404	6.91404
		Cluster 4	18.89224	18.89224	18.89224	18.89224
4	amutha1_correction16	Cluster 0	0.54939	0.59162	0.64783	0.59628
		Cluster 1	11.37485	11.37485	11.37485	11.37485
		Cluster 2	4.04826	4.04826	4.04826	4.04826
		Cluster 3	11.27297	11.27297	11.27297	11.27297

		Cluster 4	25.00564	25.00564	25.00564	25.00564
5	amutha1_grays16	Cluster 0	0.11093	3.59155	4.65886	2.78711
		Cluster 1	13.94733	44.98157	16.21350	25.04747
		Cluster 2	23.11145	44.61778	15.93065	27.88662
		Cluster 3	31.50218	43.41351	15.72048	30.21206
		Cluster 4	6.15600	3.16819	5.49215	4.93878
6	amutha1_heart16	Cluster 0	2.03467	3.51565	4.05794	3.20275
		Cluster 1	1.47175	1.37632	1.43898	1.42902
		Cluster 2	47.79306	23.46506	10.25614	27.17142
		Cluster 3	59.69168	38.33291	19.28358	39.10273
		Cluster 4	6.73483	6.65499	6.64011	6.67664

7	amutha1_invertgrayscale16	Cluster 0	58.58639	58.58639	58.58639	58.58639
		Cluster 1	19.65718	19.65718	19.65718	19.65718
		Cluster 2	11.81144	11.81144	11.81144	11.81144
		Cluster 3	4.85876	4.85876	4.85876	4.85876
		Cluster 4	5.57083	5.57083	5.57083	5.57083
8	amutha1_mag125	Cluster 0	0.52180	0.52180	0.52180	0.52180
		Cluster 1	1.67508	1.67508	1.67508	1.67508
		Cluster 2	11.49618	11.49618	11.49618	11.49618
		Cluster 3	36.93798	36.93798	36.93798	36.93798
		Cluster 4	36.59048	36.59048	36.59048	36.59048
9	amutha1_microdeltahotmetal16	Cluster 0	0.33259	10.96985	4.63209	5.31151
		Cluster 1	8.74433	11.33498	20.94943	13.67625
		Cluster 2	7.58064	5.74413	12.04368	8.45615
		Cluster 3	8.26020	4.83261	6.44729	6.51337
		Cluster 4	6.80837	4.52721	1.88230	4.40596
10	amutha1_mini08	Cluster 0	0.20644	0.20644	0.20644	0.20644
		Cluster 1	3.18826	3.18826	3.18826	3.18826
		Cluster 2	20.92129	20.92129	20.92129	20.92129
		Cluster 3	75.95297	75.95297	75.95297	75.95297

		Cluster 4	44.47972	44.47972	44.47972	44.47972
11	amutha1_mirror	Cluster 0	0.36644	0.36644	0.36644	0.36644
		Cluster 1	2.04447	2.04447	2.04447	2.04447
		Cluster 2	13.78673	13.78673	13.78673	13.78673
		Cluster 3	48.89865	48.89865	48.89865	48.89865
		Cluster 4	37.64739	37.64739	37.64739	37.64739
12	amutha1_parathyroid16	Cluster 0	0.10450	2.26166	2.15597	1.50738
		Cluster 1	30.76682	63.44990	63.92767	52.71480
		Cluster 2	15.48219	16.71205	17.90945	16.70123
		Cluster 3	32.62429	17.03605	25.60113	25.08715
		Cluster 4	9.83146	4.45430	6.65513	6.98030
13	amutha1_rainbow16	Cluster 0	0.10994	3.51031	4.51945	2.71324
		Cluster 1	23.98523	76.21647	28.31132	42.83767
		Cluster 2	23.17419	43.78645	17.60132	28.18732
		Cluster 3	31.53047	43.47549	14.93693	29.98097
		Cluster 4	6.19493	3.21063	5.51814	4.97457
14	amutha1_spectrum16	Cluster 0	0.33800	2.28777	1.33870	1.32149
		Cluster 1	7.25961	19.46313	9.64400	12.12225
		Cluster 2	23.48256	40.39170	16.40364	26.75930
		Cluster 3	33.10107	39.36426	16.19909	29.55481
		Cluster 4	11.29693	5.08213	4.51422	6.96442
15	amutha1_stars16	Cluster 0	0.19850	2.94411	4.51729	2.55330
		Cluster 1	21.04394	22.02774	24.39543	22.48904
		Cluster 2	45.14638	42.88852	44.12731	44.05407
		Cluster 3	83.42021	79.40295	80.93540	81.25286
		Cluster 4	4.49384	3.63248	3.74473	3.95702

16	amutha1_warmmetal16	Cluster 0	0.22806	1.57200	1.84753	1.21586
		Cluster 1	9.44467	7.17275	24.98245	13.86662
		Cluster 2	29.61939	5.26307	51.52801	28.80349
		Cluster 3	67.80724	23.98529	57.76281	49.85178
		Cluster 4	7.86215	1.96997	1.98318	3.93844
17	amutha1_-90	Cluster 0	0.36617	0.36617	0.36617	0.36617
		Cluster 1	2.05046	2.05046	2.05046	2.05046
		Cluster 2	13.75184	13.75184	13.75184	13.75184
		Cluster 3	49.07962	49.07962	49.07962	49.07962
		Cluster 4	36.83729	36.83729	36.83729	36.83729
18	amutha1_+90	Cluster 0	0.35769	0.35769	0.35769	0.35769
		Cluster 1	2.07034	2.07034	2.07034	2.07034
		Cluster 2	13.74811	13.74811	13.74811	13.74811
		Cluster 3	49.10721	49.10721	49.10721	49.10721
		Cluster 4	37.62007	37.62007	37.62007	37.62007

Table2: Affected density of Pixels

From the affected density value, the high value of each preprocessed and clustered result values are identified and presented as table along with each property.

	Name of the image along with the property	**High Density Cluster**	**High density Value**
1	amutha1_ascendingred16	img 3	34.21394
2	amutha1_auxctq16	img 1	73.87934
3	amutha1_bwlnvlog16	img 1	31.78129
4	amutha1_correction16	img 4	25.00564
5	amutha1_grays16	img 3	30.2120567
6	amutha1_heart16	img 3	39.1027261
7	amutha1_invertgrayscale16	img 0	58.58639
8	amutha1_mag125	img 3	36.93798

	Name of the image along with the property	**High Density Cluster**	**High density Value**
9	amutha1_microdeltahotmetal16	img 1	13.67625
10	amutha1_mini08	img 3	75.95297
11	amutha1_mirror	img 3	48.89865
12	amutha1_parathyroid16	img 1	52.7147966
13	amutha1_rainbow16	img 1	42.837672
14	amutha1_spectrum16	img3	29.5548509
15	amutha1_stars16	img 3	81.25286
16	amutha1_warmmetal16	img 3	49.85178
17	amutha1_-90	img 3	49.07962
18	amutha1_+90	img 3	49.10721

Table3: high density pixel value

Clustered image	frequency	Tot. density	Average	Index Value
img 0	1	58.58639	58.58639	**2.92932**
img 1	5	214.88935	42.97787	2.14889
img 2	**0**	**0.00000**	0.00000	0.00000
img 3	11	524.16464	47.65133	2.38257
img 4	1	25.00564	25.00564	1.25028

Table4: Index value for Amutha1

From the high frequency index value is considered for the stage determination. The same process is repeated and the final index values are determined in the remaining images.

Name	**Level of Cancer**
Amutha1	2.92
Amutha2	2.99
Amutha3	2.88
Amutha4	2.90
Average	**2.92**

Table5: Stage of Amutha1

The stage 0 is a type of evasive breast cancer. The remaining stages such as stage1, stage2, stage3 and stage4 are invasive breast cancer. Depends on the common Index value we can easily find the type of the breast cancer and the stage of the breast cancer. As per the calculation the density level size is 2.92 .

IV.CONCLUSION

Applied and computational research work contributed many ways to the medical image analysis. This research work the digital mammogram for breast cancer stage detection
using Multi view univariate classification data mining technique used to determine the stage of the breast cancer along with the affected density. The research work collected the four image and the analysis strengthen with 18 attribute pre-processing and each attribute three layer and five cluster. The determination obtained the analysis of 1080 images and its corresponding values.

Cancer **stage** is based on size of the cancer, the cancer is invasive or non-invasive, cancer is in the lymph nodes and the cancer has spread to other parts of the body beyond the breast. Stage is usually expressed as a number on a scale of 0 through IV — with stage 0 describing non-invasive cancers that remain within their original location and stage IV describing invasive cancers that have spread outside the breast to other parts of the body. Cancer stage is different from cancer grade, even though both use numbers. Cancer stage is 0 through IV. Cancer grade is 1 through 3.The stage of the breast cancer can help the doctor understand prognosis (the most likely outcome of the disease) and make decisions about treatment, along with all of the other results in pathology report. Cancer stage also gives everyone a common way to describe the breast cancer, so that the results of treatment can be compared and understood relative improvements. As a result of the affected index is 2.92,She is in the stage 3 and having **invasive breast cancer and the density level of 2.92**.

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