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A Survey on Digital Image Processing Techniques for Tumor Detection

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Abstract

The paper presents a formal review on evolution of the image processing techniques for tumor detection, comparison of the existing techniques to obtain the one which gives the best results for detection and classification of tumor. The scope of the propounded technique is semblance of the gaps by giving effectual results in identifying the tumor.

Keywords: Classification of Tumor, Oncologists, Parameters, Region of Interest, Strengths, Tumor Detection

1. Introduction

The paper aims to make a comparative analysis on different tumor detection techniques, and results are made on the basis of parameters considered, so as to find the robust algorithm for tumor detection.

The origination of the term cancer in (460-370 BC), is credited to the "Father of Medicine", Greek Physician Hippocrates. However, having its earliest evidences as osteosarcoma (bone tumors) in fossilized human mummies in Ancient Egypt (3000 BC), cancer, in accordance with latest statistics is amongst the leading causes of deaths all over the world as it's a life threatening disease.

Cancer in living beings occur when the DNA, basis of genetic code of cell gets corrupted due to an exposure to chemicals, radiations, inheritance or viruses that lead to mutation in the genetics.

The 19^{th} century was the birth of scientific oncology when Digital Images began to be used for screening and early detection of tumor and its classification into malignant or non – malignant as shown in Table 1. The concept of the images, that aroused millions of years back has its roots in nature because of its origination since the existence of a source of light, today has become of great help to the experts in detection and accurate location of tumor sites in humans which was earlier difficult due to complex pathologies.

The scope of this review is to address various image processing techniques being used for tumor detection and considering there pros and cons. On the basis of their pros and limitations it becomes relatively easy to detect tumor at a much early stage. From the literature its ascertained that the malignant tumor bear out to be dangerous and can certainly lead to death. Meticulous attempt has been made in the paper to find the robust and vigorous technique that can precisely classify the tumor as malignant or benign

2. History Specifying Relation between Tumor Detection and Image Processing

The baleful disease tumor has evolved since human beings existed. Since 2500 BC, its detection is considered a vital subject. The following table describes how tumor detection techniques have evolved over time since it existed. The techniques being used from earliest time till present era with their benefits, limitations and accuracy are discussed in Table 2.

3. Tumor Detection Process

In this section complete and the basic procedure of tumor detection by Image Processing is described with help of DFDs. In DFD level 1 the intermediate step is presented in which the region of interest is detected, by firstly pre-processing the image and then applying segmentation. After

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finding the region of interest, classification is done in order to find out whether the suspected candidate region is a tumor region is tumor or not. DFDs level 0, 1 and 2 are presented. DFD level – 0 is a simple representation of detecting tumor region in the acquired image by applying different techniques of Image Processing and Machine Learning.

DFD level 1 as in Figure 2 explains the concept behind detection of the region of interest. DFD level 2 as in Figure 3 depicts the complete procedure of tumor detection process, presenting the various techniques being used in the process. The techniques are used individually, or in combination for finding the tumor. The techniques described below also have sub techniques, which are used to detect tumor. Some of the techniques are pre-processing, template matching, neural networks etc.

As per the literature the basic techniques of image processing and machine learning being used for tumor detection are discussed below.

Table 1. Various kinds of tumors

Sl. No.	Type	Description	Threat
1	0	The tumors which does not spread to different body parts.	x
2	1	The tumors which spread to different body areas.	✓
3	X^1	The tumors which originate at a particular site in body and rarely spread to other areas	x
4	X^2	The secondary tumors are those which originated at some other locations in body but spread to other parts as well.	✓

0-Benign , 1 – Malignant , X^1– Primary tumor , X^2– Metastatic tumor, x -Not threatening , ✓-Life threatening

3.1 Preprocessing

The pre-processing operations[1,15,19] basically facilitates subsequent processing of digitized images which get contaminated with noises during acquisition process and thus image data gets corrupted, but with help of pre-processing techniques the information of all the distorted pixels can be restored.

3.2 Feature Extraction

This technique is of great importance in field of Medical Image Processing. When an image of particular body part is to be studied for diagnosis of tumor, feature extraction provides an aid by reducing dimensionality or area to be studied. This approach is also used for segmentation of images, to find ROI.

Rather than considering all the image features at once, selection and extraction of good features will lead to better segmentation results. Feature extraction[31] also plays a vital role in classification of tumors. For methods of constructing combinations of the variables feature

Table 2. Historical relation between TD and IP

Era	Author Name	Techniques/Algorithms for Tumor Detection	Benefits	Limitations	Accuracy
3000 B.C	Edwin Smith Papyrus	cauterization by fire drill	ulcer removal by tool	E_L	A_L
460 -370 B.C	Greek Hippocrates	drawing of outward tumor for detection , humour theory	cell discovery, ulcer removal by tool	R_L, No progress	M_A
1600–1700	Harvey	Autopsies	cancer cause easily detected	lacks sufficient knowledge	M_A
1700–1800	Giovanni Morgagni	lymph theory , Surgery, dissection	ulcer removal by tool	N_A	E_L
1800–1900	Muller	Blastoma theory	cancer cell detection	lacks sufficient knowledge	M_A
1900–1950	Virchow and other scientists	parasite theory, trauma andchronic iteration theory	prominent information	U_R	E_I
1950–1960	Giovanni Morgagni	microscopy images	Easy, M_A	L_{SK} ,U_R	M_A
1970	George Papanicolaou	pap test	Early detection	N_A	A_H
1970(+)	L Modalities	MRI, CT, M_M, U_S, PET	better vision, Easy	N_A	A_H

A_H -highly accurate, M_A -moderate accuracy, A_L- low accuracy , N_A -Not applicable, U_R -unreliable, less reliable. H_R- Highly reliable, M_A -less efficient

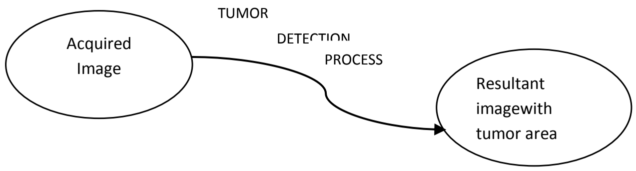
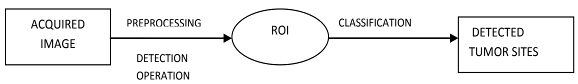


Figure 1. DFD level 0.



Region of Interest

Figure 2. DFD Level 1.

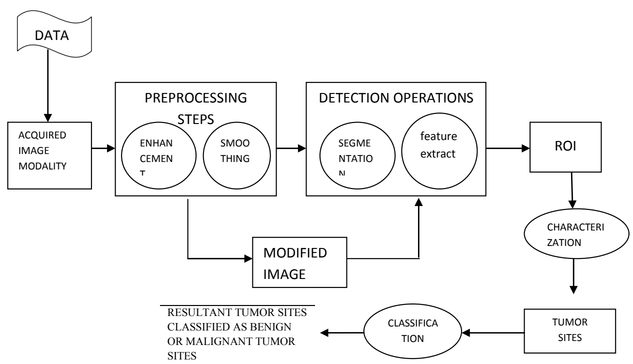


Figure 3. DFD Level 2.

extraction is a general term to get around these difficulties while describing the data with adequate precision.

3.3 Segmentation

Partitioning of digital images into sets of pixels is called segmentation. It aims to represent an image in a much simpler way, to make it easier to analyze and much more informative. As a result of segmentation set of segments[30] is acquired which covers entire picture collectively. Every pixel within a segment possess same characteristics like color, intensity, texture and label as others. In medical imaging segmentation is of extreme importance to find contour of different anatomical structures.

3.4 Classification

The definitive step in tumor detection is classification of tumor as malignant or benign tumor. Classification[34] in general involves two steps of training and testing.

3.5 Template Matching

Template matching is a technique used to verdict regions in image which are similar to template. In tumor detection process, a template is used as an aid for coarsely locating tumor by ruling out the edges. A template is created and is moved over the acquired image sequentially and the area where the templates match the image is marked. The template is always of smaller size than image. The technique is of great importance and is useful in successfully detecting tumor

3.6 Neural Networks

The concept of Artificial Neural Networks was originated from "Central Nervous System" of humans. The artificial neurons in ANN reminiscent of human neurons are basically interconnected nodes. This concept in practice since 1943 works according to the training and learning process, is of the essence in field of medical imaging and is used for enhancement of images and classification of tumors. It has helped to make the tumor detection process automated

4. An Overview of Some of the Existing Techniques for Tumor Detection

As we know from history, that tumor is life threatening for humans, therefore, its early detection and treatment is necessary as it would increase the survival chances of the patient. Presently, many imaging modalities exist which are being used by radiologist for visualization of the internal structure for detecting various diseases without performing surgery. According to the latest statistics there are around 14.1million cases of cancer around the world every year. This poses the biggest challenge to the radiologists who manually locate the lesions on different modalities. Thus, an accurate computer aided clinical tool is an imperative necessity in order to assist the experts detecting tumor.

As mentioned in Table 3 above there are various techniques which were used to detect tumor since 3000 B.C. Some of the techniques were very effective, while certain procedures led to the need of developing robust techniques.

Over the centuries there was a great change in beliefs towards the disease which had a major impact on the advancement of techniques for detecting tumor. Years later in 19th century images began to be used to diagnose tumor

In[1] proposed an approach to augment the segmentation for extracting suspicious mass areas from mammograms. The paper focused on automatic detection of all possible lesion sites by using Enhancement and model selection, A morphological operation "Dual

Table 3. Different techniques used for tumor detection

Sl.No.	Era	Techniques Used	Accuracy
1	3000 B.C –1600	cauterization by fire drill humor theory	E_L
2	1600 – 1900	lymph theory, Surgery	N_A
3	1970 – 1980	Blastoma theory	A_L
4	1981 – 1990	advanced techniques	100 %
5	1991 – 2000	more advanced techniques	A_S
6	2000 – 2010	advanced techniques	E_D, H_A
7	2010 – 2015	more advanced techniques	adhere to time and cost

B_C basic, A_D advance, A_S – accurate satisfaction, E_L- less efficiency, H_A- high accuracy, A_L – low accuracy C_F – cauterization by fire drill

Morphological Operation". Histogram models, FGGM distribution to determine the Kernel shape and number of regions in image.

In[4] presented work on techniques for detecting circumscribed masses in mammograms. In the initial step mammograms were enhanced by removing noise in background while preserving the edges.

In[3] presented a review on all the components of image analysis system which includes four steps – Pre-processing, Feature Extraction, Segmentation and Classification, used to MR detect Glioblastoma and evaluated the results in all the cases as shown below in Table 4.

In[5] proposed a method to detect masses in mammograms and classifying them as benign and malignant by using texture field analysis. Success rate of 100% was achieved.

The pre-processing techniques used for enhancement were Gaussian low pass filter and Pyramidal Decomposition, which helped to smoothen the image.

In[6] proposed an algorithm for unsupervised color segmentation with appliance to skin tumor.

By using color feature to detect tumor border, author put forward an algorithm[5] which involved noise removal with Pseudo Median Filter and non skin masking algorithm.

The Table 5 presents all the algorithms used with their average error and standard deviation.

In[7] proposed a filter for detection of lung nodule on chest X-Rays, three kinds of CI filters had been investigated and experimentally evaluated. Different characteristics of CI Filters Adaptive Ring, Coin and Iris were discussed in detail .

In[8] proposed a technique to detect tumor by measuring abnormal thickness in bladder wall by taking the mean and standard deviation. The Table 6 below presents the comparison of automated and manual process.

Table 4. Summary of experimental results

Sl. No.	Parameters	Results
1	No.of films tested	17
2	No. of candidate sites	19
4	Average no. of candidates per film	1.1
5	Hit rate	100%
6	False alarm rate	1.7

Table 5. Error metric average and S.D

Algorithms	Average Error	Standard Deviation	Tumors Error < 1
ATS	0.665	0.336	40
CSS	0.797	0.332	25
MRS	0.770	0.330	42
SMS	0.782	0.338	23
FCS	0.702	0.330	42
MCS	0.524	0.372	46
CM	0.367	0.226	57

ATS -Adaptive thresholding, CSS -centre split, fuzzy-c mean, MCS -PCT median, SMS split and merge, MRS –multi resolution , CM -combined method

Table 6. Comparison of automated and manual process

Comparative Analysis	Expert detects tumor	No tumor detected by expert
S/W Detects tumor	TP = 16	FP =17
S/W does not detect tumor	FN = 2	TN = 123

TP- true – true negative, F positive, FN – false negative

Thresholding and marching cubes algorithm were used for segmentation, a normal thickness atlas with average and other with Standard deviation was constructed[8].

In[9] presented a CT liver image diagnostic system to unearth the liver boundary and tumors in liver. To extract the liver boundary segmentation approach "Detect Before Extract" was used. The desired liver boundary was achieved by using Deformable Active Model (contour modification model). Classification system developed on basis of MPNN (Modified Probabilistic Neural Network) was applied for discrimination between heptoma and hemageoma liver tumor. The classification system used in this paper is Texture –Feature based which used features.

In[2] proposed a technique to recognize nodular tumor in chest radiographs by using a Ladder Structured

Decision Tree. The anticipated Ballard approach involved three major steps:

1) Digitization of radiographs
2) Enhancement or pre-processing operations which results in edge detection.
3) Recognition of tumor and its classification. The technique used gave accurate and comparable results. The algorithm is explained as follows.

Recognition of Tumor and its Classification

```
Initialize Image data set I_SET = 1 to n
If I_SET(n) = P × P            // where P × P is required limit of
                                  upper dimensions set for the image
                               under test
{
   For ( I_SET(n) =1, I_SET(n), I_SET(n) ++)
     {
       Digitize the Image
       S_n = Σ_{n=1}^{n} I_SET(n)     // where S_n sample for the image
                                          under test
         Check the value of S_n
If (S_n = 1 or 0 )
           {
             Find node N_n
              S_n ε N_n
             }
         Else
             Change I_SET(n ) dimensions;
     }
   If ( N_n = T_Nn)              // T_Nn – Test node or candidate node
   Do
     {
       Classification C_set 1
       C_set, 1 = Σ_{n=0}^{n-1} N_n
      }
   While N_n = n
   Do
     {
       Classification C_set 2
     }
   Check
       If ( C_set 2 = T_U )            // T_U =upper threshold
{
         malignant or tumor
         }
       Else if
         ( C_set 2 = T_l )               // T_l = lower threshold
           {
            non malignant or tumor
           }
   Else
     Exit
}
```

In[10] proposed an approach to detect lesion in liver. Median filtering was used to reduce noise in image while contrast information was retained. To determine closed and accurate contours Snakes/Active contour method was used. The following Equations describe the snake model.

$$E_{snake} = E_{internal} + E_{external} \tag{1}$$

Energy minimization splines Snake models are guided by internal and external forces. $E_{internal}$ is comprised of the continuous energy and energy of curvature and the $E_{external}$ is composed of the image energy and other constraints enforced by user.

$$E_{snake} = \alpha E_{Cont} + \beta E_{curv} + \gamma E_{image} \tag{2}$$

Equation (2) depicts the discrete form of the snake equation. E_{Cont} represents the energy because discontinuities.

The energy due to discontinuities as follows.

$$E_{Cont} = d_{av} - |v_i - v_{i-1}| \tag{3}$$

In Equation (3), d_{av} represents the average distance between two snake points which are neighbors.

$$S_{lesion} = (T_{V1} - G(x, y))/(T_{V1} - T_V) \tag{4}$$

$$S_{liver} = (T_1 - G(x,y))/(T_{L1} - T_{VL}) \tag{5}$$

Two fuzzy sets corresponding to fuzzy edge region and fuzzy smooth region, $S_{lesion,}$ S_{liver} were constructed using the two new thresholds $T_{V1,}$ T_{L1} which have equal space between them and the gradient magnitude values using sobel operator.

In[11] proposed an approach for early detection of skin cancer and measuring the vascularisation and pigmentation in Nevoscope images. Pre-processing pace involved resizing, masking, cropping, hair removal and converting RGB to Gray scale images. The different segmentation techniques used were Sigmoid mapping, Fuzzy C Mean , Principle component transform. The best segmented image out of three was selected by considering the correlation coefficient, edge strength and lesion size. Transillumination image was used for classification of tumor as benign or malignant.

In[12] proposed an algorithm for segmenting brain to detect tumor using alignment based features. The preprocessing pipeline was used which included: 1. Non linear filtering for noise reduction, 2. Inter – Slice intensity variation correction, 3. Intra volume intensity bias field correction, 4. Alignment of different modalities 5. Linear alignment of modalities with template, 6. Non linear warping of modalities with template. 7. Re-sampling of voxels to template coordination system (B – Spline). 8. Weighted regression for inter volume intensity standardization[12]

In[13] presented a novel approach in this paper for detecting brain tumor in MR images. Abnormal tissues were detected using co-variance method and (Principle Component Analysis) PCA.

In[14] proposed a technique for characterization of brain tumors. The presence of tumor can be determined by any of PCA, ICA, ISOMAP algorithms. In the pre processing stage enhancement and resizing of 113 3D MR images was done. The position of tumor was manually indicated by experts, median intensity was used for having all intensities in same range. Gentle Adaboost algorithm[14] was used for training the classifier which used intensity based features, gabor features, symmetry features.

Adaboost algorithm gave the best results for classification of tumors as benign and malignant. The results obtained by the algorithm are comparable.

The proposed technique is suitable for part based segmentation.

In[15] proposed a Pre-Operative and Post-Recurrence method for brain tumor registration. PORTR works on facts that all scans are from same patient. Minimum of energy function is used to determine the deformation between two scans. The pre-operative and post recurrence scans of 24 patients were experimentally registered based on discrete optimization, ANTS, Attribute vectors, Mutual saliency. The method gives accurate results the future work can be done to enhance the algorithm for even better results.

Algorithm_Hybrid_Optimization

```
Begin
Initialize Base solution B_sol
    For (B_sol =1, B_sol< B_sol(final) , B_sol ++)
      {
        For each B_sol(n)      // where B_sol(n) is the solution
        for n task
            {
M_sol =1, M_sol< M_sol(final),M_sol ++)
}
      }
    If
      {
        B_sol(n)= M_sol(n)
        Target meet
      }
  Then
      Update B_sol
      Apply O_P
// Where O_P optimization for
         N intervals and O_P € B_sol(n)
    Check
      Exit(1)
    Else
      {
        Converge and Change M_sol
        Exit
      }
End
```

In[16] proposed a technique for tumor detection in cervical tissue. Microscopy images were used, Ki-67 was used to provide assistance in tumor detection process. Anisotropic Diffusion was employed for noise removal since it preserved the edges Firstly the abnormal nuclei were detected, then all the touching nuclei were detected and the other regions.

Finally all the tumorous cell were detected as the nuclei of the tumorous cells is always of larger size than the other .

In[17] proposed a speculation detection method, which is of great importance in characterizing malignant tumors. 3D ultrasound was used for detecting speculation encasing breast tumor. Morphological operations and ROSE Algorithm were used for region selection. STICK Algorithm was used for ultrasound segmentation.

$$i-\sum_{1}\frac{xI(x,y)}{N},j-\sum_{1}\frac{yI(x,y)}{N} \tag{6}$$

After applying the thresholding method, the pixels were separated into regions based upon their intensity difference.

The region which comprised the centre of the image was selected. In the equation above the binary image is represented by I(x,y), (I,j) signify the centre and N is the number of marked pixels.

$$\frac{\partial i}{\partial r}-\frac{\partial i}{\partial x}\frac{\partial x}{\partial r}+\frac{\partial I}{\partial r}\frac{\partial y}{\partial r}-I_x\cos\cos\phi+I_y\sin\sin\phi \tag{7}$$

For the segmentation of the image, gradient of image and orientation structure is calculated. The gradient is given by and can be represented as in Equation (2), and the orientation structure is given by -

$$\theta(x,y)-\tan^{(-1)}\frac{I_x}{I_y} \tag{8}$$

In case of the ultrasound images the method for segmentation described above does not work.

Therefore, Stick Algorithm was used which is based upon sticks, line segments in different angular orientation.

The corresponding angle and orientation is calculated as in Equation (4) and (5) respectively –

$$(i - 1)\pi/(2n - 2) \tag{9}$$

$$\theta_j - (i_{\min} - 1)\pi/(2n - 2) \tag{10}$$

In[18] used phase contrast images and machine learning approach for detection of tumor cells. Super pixel labeling was used for processing. Simple Linear Iterative Clustering (SLIC), and K-mean clustering was used for segmentation and SIFT for extracting features. CS- LBP was employed for region description. Random Forest Classifier was used for classification.

In[19] put forward an approach to detect ROI, by using morphological band pass filters in digital mammograms.

Multi level morphological operations were used for pre processing of mammograms ROI was detected by applying thresholding method. Binary morphology operators were used for refinement process. The technique gives more accurate results than DWT.

In[20] proposed an algorithm for classification of mammograms grouping them into three categories benign, malignant, normal.

$$\text{SENSITIVITY} = \text{TP} / \text{TP} + \text{FN} \tag{11}$$

$$\text{SELECTIVILTY} = \text{TP} / \text{TP} + \text{FN} \tag{12}$$

In[21] in their work used a set of 251 digitized images. Automatic induction was used for producing classification Artificial intelligence concept was used for classification of tumors.

The study[21] aspired to prove that different features extracted from colored skin tumors are sufficient to distinguish the benign tumors from malignant.

The major aim was to precisely find the malignancy of the tumor since it is deadly for the patients suffering from cancer.

Results of the algorithm are presented in Table 7, 8 and 9.

In[22], proposed a method for classification of breast masses by image processing techniques. During the pre processing step, different techniques like Anisotropic Diffusion Filters and Gaussian filter were used for removing noises.

Table 7. Results of the approach

Sl. No.	Kernel Function	Sensitivity	Specificity
1	Gaussian RBF	92.7%	90
2	polynomial	89%	90
3	linear	88%	89

Table 8. Pixels in the boundary of detected tumor for various segmentation methods

T_D	No. of pixels in the boundary of detected tumor by			
	M_S	$M.T_{R.G}$	$C.A_{E.D}$	P_M
T1: L_S	223.625	N_d	195.875	195.875
T 2: L_S	116.125	70.375	84.5	100.25

M_S- manual segmentation, $M.T_{R.G}$- modifiedtexture based region growing, $C.A_{E.D}$ - cellular, automated edge detection, P_M – Proposed method, T_D- tumor detection, T1: L_S -tumor 1 large sized, T 2: L_S- tumor 2 large sized, N_D- not detected

Table 9. Coefficient of similarity and spatial overlap of modified texture based segmentation

BT.DM	Coefficient of Similarity	Spatial filter
M.TR.G	0.60	0.75
PM	0.80	0.92

M.TR.G- modifiedtexture based region, PM – Proposed method

To obtain a closed Boundary of contour of speculated mass, Active Contour Model[22] was used.

In the Final step classification is performed using shadowing features and shape features by Support Vector Machine[31]. The technique is non- invasive and cost effective. The Table 7 below describes the result of the approach.

In[23] proposed an approach for tumor detection in brain by using Texture based region growing and Edge detection techniques. MR images were used. Various techniques Gray level conversion, resizing of image, median filtering, high pass filtering[37] were applied for pre processing. After pre- processing all the noises were removed from the image which gave better results in detection of tumor[23]. Modified texture based region growing was used for segmentation. Moore neighbourhood method was employed for edge detection of cells. The results obtained are presented in Table 8, 9, 10.

In[24] proposed an automatic diagnostic system for detecting pulmonary nodules in CT images. The images are pre-processed and enhanced. On the basis of medical knowledge three rules are generated which used the features for classifying the candidate nodules as tumors or non tumor.

In Table 11, comparison has been made between results from physicians and CAD system. The results are compared on the basis of physician in agreement with results from CAD system.

In[26] proposed a new fusion model for classification of lungs tumor by using Genetic Algorithm.

The CT images were pre- processed using median filter[32] and morphological operators.

Texture analysis and a novel fusion MAD technique were used for feature extraction.

Genetic Algorithm was utilized for selecting features and K – Nearest neighbour[34] multilayer preceptron –NN[33] for classification of tumor as benign ormalignant. In Table 12, complete detail of classification of lung tumor. Table 14 performance of different classifier is discussed as emphysema, bronchiestasis, pleural effusion and normal is presented in case of different classifier.

Table 10. No. of pixels for different edge detection methods integrated to modified texture based region

Integrated edge detection methods	PIEDIT	Pixels in edge of detected
SL	117.75	88.25
RT	164.25	91.375
PT	119	87.625
CY	111.25	88.250
CA	195.875	100.25

SO – spatial Overlap , SL- sobel filter, RF- Robert filter, PIEDIT-Pixels in edge of detected,

Table 11. Comparison between physician results and CAD system

	No. of doctors		CAD SYSTEM		
	N_{0D}	no. of modules	class 1	class2	false negetive
E- Definite	A_{L3}	1	1	0	0
	B_Y 2	2	2	0	0
	B_Y 1	8	8	0	0
D – suspicious	By 3	10	10	0	0
	B_Y 2	42	36	5	1
	B_Y 1	167	117	28	22
	TOTAL	230	174	33	23

The no. of correctly identified cases are mentioned. In Table 13, accuracy in terms of percentage in case of different feature selection and extraction technique is mentioned.

Genetic Algorithm _Tumor Detection

Initialize $I_{SET(n)}$
For ($I_{SET(n)}$ = 1, $I_{SET(n)}$< $I_{SET(last)}$, $I_{SET(n)}$ ++) // n= 0 to 1
{Apply M_f
If (M_f = 1)
{
Apply smoothening
}
Else
Exit (1)
} // M_f – median filter
For (S_{IMAGE} = 1, S_{IMAGE} < $S_{IMAGE(last)}$, S_{IMAGE} ++)
{
Create F_{VECTOR}
}
Extract selected features using G_A
If
{
F_{SELECT} > T_H
(T_H = Minimum threshold level through G_A)
Apply classification
else If
{ // S_{IMAGE} = smoothen image
F_{SELECT} = T_L
Apply J48
Else if
{
F_{SELECT} = T_M // (S_{IMAGE} ε F_{VECTOR})
Apply KNN
} // F_{SELECT} ε F_{VECTOR}
Else
{
F_{SELECT} = T_H
Apply MP-NN
} }
Perform Evaluation
}
End

Table 12. Classification details disease wise

classifiers	correctly classified as emphysema	correctly classified abronchitis	correctly classified pleural effusions	correctly classified anormal disease
GA_J48	87	85	82	84
GA_KNN	87	88	85	87
GA_NN	92	91	90	92

Table 13. Classification a acuracy (in percentage)

Feature extraction technique	J48	KNN	MLPNN
GF &GA	77.19	72.88	85.96
WHT&GA	72.88	74.58	77.19
PF &GA	83.05	86.44	91.53

Table 14. Performance measures for various classifiers

T_S	J48			K-NN			MLPNN		
	$P_N R_L F_M$			P_N	R_L	F_M	P_N	R_L	F_M
G_F & GA	0.75	0.78	0.78	0.72	0.71	0.71	0.84	0.86	0.85
W_{HT}& GA	0.72	0.71	0.73	0.75	0.75	0.75	0.75	0.78	0.77
P_F & GA	0.83	0.83	0.72	0.88	0.86	0.87	0.92	0.91	0.92

P_N- Precision, R_L – recall, F_M- feature measure, K-NN – K nearest neighbour, G_F- gabor filter, W_{HT}- wals hadamard transform,GA-genetic algorithm, P_F-proposed fusion

In[25] applied an Artificial Neural Network for detection of breast tumors detection in mammograms. SOM was used for reducing the Dimensionality. SVM kernel based approach was used for classifying the tumor as benign or malignant. For interaction between various variables MARS was used. Sensitivity, Specificity, Youden index Accuracy were used as performance measures. Clustering algorithm were widely used as exploratory tools for analyzing the breast cancer data. Nevertheless, there are certain limitations in case of clustering algorithm. In, clustering algorithm based on SOM[36] was used for pre-processing the information in the samples of breast screening programme.

The performance measures considered are sensitivity, accuracy, specificity[35] and Youden index. The MARS model, used for modeling as it builds models piecewise by using linear regression. The performance of MARS model is discussed in Table 15 above taking specificity and sensitivity as performance measure. Table 16 and 17 presents the confusion matrix and performance measures of SVM model.

The death rate of cancer patient was too high in earlier times but now with much awareness the mortality rate has decreased as different techniques have been developed for early many technique have been developed since 3000 BC when there was no cure for the baleful disease.

The development of these techniques have lead to decrease in the mortality rate of the cancer patients. Ever since tumor existed the techniques have evolved and have been improved for better results. There are different techniques developed for detecting tumor with varied accuracy and hit rate.

Table 15. Specificity and sensitivity of the MARS model

SOM	Cancer Patients	MARS Model	True Healthy	FSick,	False Healthy	Specificity	Sensibility
36	100	1	931	100	0	01.9	100
64	100	2	16.83	91	9	34.0	91.0
100	100	3	27.16	74	26	54.9	74.0
121	100	4	27.39	73	27	55.3	73.0
144	100	5	34.17	63	37	69.0	63.0
169	100	6	45.14	63	37	71.0	63.0
196	100	7	35.77	61	39	72.3	61.0
225	100	8	42.93	43	57	86.7	43.0
484	100	9	46.78	28	72	94.5	28.0

Table 16. Confusion matrix for the three different SVM models

SVM Model	Training set	TP	TN	FP	FN
1	144 + 100	51	39,688	9713	49
2	169 + 100	99	30,129	19,272	1
3	196 + 100	100	34,109	15, 328	0

TP- True positive, FP- false positive, FN- false negative, TN- true negative

Table 17. Performance measures

SVM Model	Training set	Specificity	Sensitivity	Accuracy	Youden Index
1	144 +100	0.8034	0.51	0.08028	0.3134
2	169 +100	0.6099	0.99	0.6107	0.5999
3	196 +100	0.6886	1	0.6893	0.6886

Table 18 compares the different techniques based upon their accuracy, sensitivity and specificity. Depending on their accuracy, the suitable algorithm can be easily determined, which will lead to the accurate detection of tumor.

The techniques with less accuracy rate, sensitivity and specificity can be worked upon for enhancement.

5. Methods and Material

The section presents a detailed review of different techniques being used for tumor detection over decades.

Techniques being used since 1970's till 2015 have been considered. The pros and cons of the techniques being used are also discussed. The accuracy and results of different techniques are mentioned. The section is divided into 3 parts representing techniques between 1970-2000, 2000-2005, 2005-2015. The techniques used between 1970–2000 are described in detail in Table 19.

Table 18. Comparison of different techniques

Sr No.	Techniques Used	Problem	Sensitivity	Accuracy
1	Fuzzy reasoning	M_D	85	M_{A} , L_R
2	combined intensity	M_D	74	$A_{L,}$ L_R
3	bilateral subtraction technique	M_D	82	M_{A} , L_R
4	morphology A_H	M_D	87	S_A
5	CAD	$R_{B.P.P}$	84	M_{A} , L_R
6	FSVM	$M_{D,}$ M_C	89	S_A
7	histogram equalization	M_C	90	H_A
8	SVM	$M_{D,}$ M_C	93	$V_{H.A}$

M_A - Moderate accuracy, L_R - less reliable, S_A - satisfactorily accurate, $V_{H.A}$ - very highly accurate, H_A - high accuracy, M_D - miss detection

In Table 19 all the techniques been used for detecting tumor between 1970's and 2000 have been discussed. The period between 1995-1998 was a revolutionary era in the field of tumor detection, ample work was done as there was widespread awareness about the disease. Most of the work was driven on the modalities – mammograms, CT scans. The results were comparable but the technique could be improved.

All the techniques were able to detect the tumor but efficiency was low. In the year 1999 there were many techniques akin to the methods developed during 1995-1998 were developed with high success rates. Many novel techniques for detecting tumors were proposed as discussed in this era, but with a need of enhancement as many of the techniques developed did not adhered to time and cost and also were less efficient. Thus initiative can be taken to enhance these techniques. Table 20 describes all the techniques used between 2000–2005. The year 2004 was period of revolution in the techniques being used for tumor detection.

Many techniques with high accuracy rate were presented.

During this era there was an emerging trend towards the development of tumor detection tech-

Table 19. Comaparision of different techniques used between 1970–2000

Year	Name of Author	Modality	Techniques Used	Cancer Types	Pros	Cons	Results
1976	Dana H. Ballard[2]	Radiographs	Top down heuristics, Bottom up programming	L_G	No false positive	$N_{S,}$ relatively slow	adhere to time and cost
1989	Shuk Mei Lai[4]	Mammograms	segmentation techniques review , cross correlation	B_C	satisfactory noise removal result obtained encouraging	$N_{E,}$ no stability	100% S_R
1995	L.P Clarke[3]	MRI	median filter, template matching, FCM, K-mean, ISODATA,	B_R	best method for cost, B.M_{T-} best method for time	N.P_{RT}	M_A
1995	Arve Kjoelen[21]	CT-scan	Artificial neural network	S_C	$A_{E,}$ good results	$N_{S,}$ R_S	$H_{A,}$ 70% S_R
1996	Gregory A. Hance[6]	C_{DP}	PCT, morphology, fuzzy c mean	S_C	$E_{T,}$	$N_{C,A,}$	86% -S_R
1998	E-Liang Chen[9]	CT-scan	Detect before extract, normalized Brownian features, MPNN	L_V	object oriented, precise extraction of liver contour,	N.P_{RT}	83% S_R
1998	K. Kanazawa[24]	CT-scan	Thresholding , active contour model, morphology	L_C	Satisfactory results	$N_{C,A,}$ N.P_{RT}	80% E_Y
1999	Jun Wei[7]	X rays	Chain code filter, intensity features	L_G	$E_{T,}$ detect candidate regions	N.P_{RT}	H_A

M_I – MRI, M_M – Mammograms, U_D – Ultrasound, R_D – Radiographs, X_R – X-rays, C_T – Computed tomography, M_{YI} –Microscopy images, N_{I-} Nevoscopic images, E_{PI} – Echo planar images, C_{DP} –Colored digitized photograph , L_G – lung cancer, L_V – liver cancer, S_{C-} skin cancer, B_C -breasts cancer, B_R -brain cancer, N.P_{RT} -no procedure for real tumors, $N_{C,A}$ -not completely automated, N_E -not efficient, L_R - less reliable, S_{R-} success rate, accurate , H_A -highly accurate, M_A -moderate accuracy

Table 20. Comparision of different tumor detection techniques between 2000 -2005

Year	Name of Author	Modality	Techniques Used	Cancer Type	Pros	Cons	Results
2001	Huai Li[1]	M_M	dual morphological operation, histogram by FGGM,CBRL	B_C	A_S Fast ,robust	inefficient	S_{PR} 97% S_Y
2001	Naga R. Mudigonda[5]	M_M	gaussian low pass filter, pyramidal decomposition isomap, BMDP-7M	B_C	S_{Y-} 81% $A_{S,}$ Fast ,robust	$C_{H,}$ I_N	$S_{R(1)}$-100% $S_{R.(0)}$ -63%.A_Y
2003	Sylvain Jaume[8]	C_T	thresholding, sigmoid, high pass filtering	B_L	Best vision,A_S	time consuming,	89% $S_{Y,}$88% S_{PY} 98%
2004	Chetan Kumar[10]	E_{PI}	median filtering Region growing	L_V	Fast robust	N_A	E_T
2004	G. Zourdakis[11]	N_I	FCM ,PCT	S_K	Fast robust	$E_{L,}$ low specificity and sensitivity	S_R 95%
2004	JuCheng Yang[19]	M_M	morphological band pass filter thresholding , $B_{M,}$ D_S,M_T	B_C	$H_{E,}$ A_S	N_A	Adhere to time and cost
2004	Sheng–Fang Huang[17]	U_D	thresholding , histogram equalization, M_{O-}morphological operation ROSE A,STICK A	B_C	H_E	Used only on large data sets I_N	$S_R(_1)$ -90% S_R(0) -16%
2005	Mark Schmidt[12]	M_I	AB feature intensity, spatial intensity - average intensity maps, left right symmetry, SVM, Median filter	B_T	M.$L_{U,}$ A_R	$R_{I,}$ $N_{A,}$ E_L	E_T

E_T -efficient, S_R success rate, H_E -highly efficient, S_{PY} -specificity, C_H -cost high, N_{A-} not applicable, S_Y -specificity, I_{N-} inefficient

niques. All the techniques used between 2000-2005 gave accurate results but certain techniques lacked efficiency and needed improvement. . In[1], proposed a method to detect masses by enhancement of image using morphological operations and contextual segmentation. 97% specificity was achieved. In[10] in 2004, proposed an algorithm for detecting the tumors in liver. In[11], used nevoscopic images for detection of tumor and got comparable results. In[19], used mammograms to detect tumors. Morphological band pass filters, texture growing and many other approached were used in the process. The technique developed adhere to time and cost. In[17] used ultrasound images to detect the breasts cancer. The techniques achieved 90% of accuracy. The major drawback was the low accuracy rates in detection of benign tumors. Further enhancement of the techniques should be done in order to obtain the best and accurate results.

The technique could be enhanced in future. In[26] used genetic algorithm artificial neural network k-nearest neighbour approach mad for tumor detection and many features for feature based classification of tumor with accuracy.

The technique proposed is strong to detect tumor but can be improved for classification purpose in the field.

The Table 21 presents all the techniques being used between 2005–2015.

The latest techniques being used for detection are discussed with their pros and cons.

The limitations of the techniques are taken into consideration, in order to improve their efficiency by putting more emphasis on them. In[20] proposed an algorithm of detecting the tumor and classifying it by using decision forest classifier. The technique achieved the success rate of 90%.

In[16] used microscopic images to detect the abnormal cells based upon the tumor detection marker and separating their contours. The hit rate of the technique used was 95%. In[25] proposed an algorithm to find tumor in breasts by using mammograms. Different techniques like

Table 21. Comparision of different techniques for tumor detection between 2005–2015

Year	Name of Author	Modality	Techniques Used	Cancer Types	Pros	Cons	Results
2006	Vibha L.[20]	M_M	DFC, $H_{E,}$ $V_{E,}$ $R_{D,}$	B_C	R_M	$M_{E,}$	90.45%
2010	Yue Cui[16]	M_{YI}	Ki-67, , K-mean , Otsu	C_V	S_Y , E_M	$E_{L,}$	$S_{R(A.N)}$93.55%, $S_{R(N.N)}$ - 95.8%
2010	L . Alvarez[25]	M_M	ANN, SOM, SVM,MARS	B_C	better vision ,M_E	N_A	$H_{A,}$ G_R
2012	Sarah Parisot[14]	3D M_I	PCA, ICA , adaboost , activecontour method	B_R	novel method to encode prior knowledge to segmentation	N_A	S_T
2012	Minavathi[22]	U_S	Gaussian filter, active contour SVM	M_D	M_A	N_A	$G_{R,}H_A$
2013	Dongjin Kwon[15]	M_I	POTR, geodesic distance, ANTS	B_R	E_T, highest dice scores, plausible deformations	time consuming,	A_Y
2014	Mohmed Gauskir`[13]	M_I	PCA , Geodesic distance	B_R	used on large data sets Real time	Used only on large data sets	S_T.
2014	Neslihan Bayramoglu[18]	M_{YI}	k-mean clustering, SIFT,SNR	S_K	E_L	N_A	A_Y
2014	Charuth S.[23]	M_I	Region growing median filter.	B_R	A_S	$E_{L,}$	S_T.
2014	C. Bhubneshwari[26]	C_T	MLPNN, KNN, MAD, median filter	L_C	$G_{R,}$ H_A	N_A	$H_{A,}$ G_R

M_R moderate reliability, S_{Y-} satisfactory, A_{Y-}accuracy, G_{R-} good results. H_{A-} High accuracy, L_{E-}low efficiency S_R success rate, $M_A$moderate accuracy,M_E moderate efficiency

artificial neural network, support vector machine, self organizing maps, MARS is used. Accurate results were obtained. In[14] proposed an algorithm for detecting tumor in brains by using 3D MRI scans of patients. The different techniques used PCA, ICA, ISOMAP, ADABOOST, led to the accurate detection of tumors in brain. Satisfactory results were obtained.

6. Scope of Work

From the extensive literature survey, its observed that an automation system is entailed for detecting and classifying tumor efficiently. The technique, AVG, proposed for detection of tumor is an amalgamate of adaboost and genetic algorithm.

AVG

Function(GA_Ada_Tumor Detection)::Function (Training)
Initialize $I_{SET\ (n)}$ // n = 0 to 1
For ($I_{SET\ (n)}$ = 1 , $I_{SET\ (n)} < I_{SET\ (last)}$, $I_{SET\ (n)}$ ++)
{
Apply M_f
If (M_f = 1) // M_f – median filter
{
Apply smoothening
}
Else
Exit (1)
}
For ($S_{IMAGE\ =}$ 1, $S_{IMAGE} < S_{IMAGE(last)}$, S_{IMAGE} ++) // $S_{IMAGE\ =}$ smoothen image
{
Create F_{VECTOR}
}

```
    Extract selected features using G_A          // (S_IMAGE ε F_VECTOR)
      If                                         // F_SELECT ε F_VECTOR
        {
          F_SELECT > T_H
      (T_H = Minimum threshold level through G_A)
        Apply classification
      else If
        {
          F_SELECT = T_L
Apply J48
      Else if
        {
          F_SELECT = T_M
        Apply KNN
        }
      Else
        {
          F_SELECT = T_H
        Apply MP-NN
        }
        }
    Perform Evaluation
  }
End
```

Function(Training Parameter $I_{SET\,(n)}$, vi.j)::Function(Cascaded)

Initialize $I_{SET\,(n)}$ and weights $v_{i,j}$ = 1/2p , 1/q for y = 0,1

Where p and q are the no. of negatives and positives respectively.

For (t = 1, t< T, t++) // i = 1 to n

{

Normalize the weights , $v_{t,,i} = w_{t,i} / \sum_{j=1}^{n} v_{t,j}$

Weight error of weak classifier (h f(x, f, r, θ) is

$$C_1 = \sum_{i=1}^{n} v_i \,|h_f(x_i - y_i)|$$

}

For (C_1 =1, C<C_h, C_1 ++)

{

Select c_{best} (best classifier)ε w_{error}

$\varepsilon_t = \min_{r,f,\theta} \sum_{i}^{n} v_i$ |h(x_i, f , r, θ)| or efficient implementation

// where f_t, r_t, and θ_t are the minimizers of ε_t

}

If

{

$h_t(x)!=0$

select the value for $h_t(x) = h\,(x, f_t, p_t, \theta)$

Update the $v_{t,,i}$

$C_{1(x)}$=1 or 0

$$C1(x)\varepsilon \sum_{t=1}^{T} = a_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} a_t$$

}

Else

Exit

Function(Cascaded parameter f,d)

Initialize $f_{positive}$, $d_{minimum}$

// The maximum acceptable false (positive) / total layer and d minimum acceptable detection rates / total layers */ while F_i > Ftarget

If

{ –i ← i + 1

Fi> Ftarget. // where *P and N Positive and Negative example* –ni = 0; F_i – F_i – 1

Update weights

– while F_i > f x F_i - 1

Evaluate the current values of *ni ← ni + 1

*/

}

Else check the values of *Fi*

//Where i = 1 to n where n is number of parameters or features

End

7. Conclusion

The papers endeavoured accomplishment of a partial survey on diverse tumor detection techniques for different modalities. A comparative analysis is made on various techniques. After evaluating various approaches, the methods which can efficiently and accurately detect tumor are mentioned in results. The paper puts forward a new algorithm which is an amalgam of adaboost and genetic algorithm proposed to focus on accomplishment of more accurate results than existing techniques. The work will be extended for building new algorithm for tumor detection with an aim to reduce the computational time and implementation cost. As detecting tumor is a very complicated and sensitive task, accuracy and reliability are of much importance. Thus, a sophisticated technique that highlights new vistas for developing more vigorous image segmentation technique for tumor detection is much sought after

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