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Lung Tumor Segmentation Using Marker-Controlled Watershed and Support Vector Machine

Surbhi Vijh, KIET Group of Institutions, India
https://orcid.org/0000-0001-7038-5944

Rituparna Sarma, KIET Group of Institutions, India
https://orcid.org/0000-0001-8589-5613

Sumit Kumar, Amity University, Noida, India

ABSTRACT

The medical imaging technique showed remarkable improvement in interventional treatment of computer-aided medical diagnosis system. Image processing techniques are broadly applied in detection and exploring the abnormalities issues in tumor detection. The early stage of lung tumor detection is extremely important in medical research field. The proposed work uses image processing segmentation technique for detection of lung tumor and the support vector classifier learning technique for predicting stage of tumor. After performing preprocessing and segmentation the features are extracted from region of lung nodule. The classification is performed on dataset acquired from national cancer institute for the evaluation of lung cancer diagnosis. The multi-class machine learning classification technique SVM (support vector machine) identifies the tumor stage of lung dataset. The proposed methodology provides classification of tumor stages and improves the decision-making process. The performance is evaluated by measuring the parameters namely accuracy, sensitivity, and specificity.

KEYWORDS

Feature Extraction, Image Processing, Lung Tumor, Marker Controlled Watershed Transform, Support Vector Machine

1. INTRODUCTION

Lung tumor is a progressive disease containing abnormal cells leading to cancer. The abnormality present devastates the proper regular performance and functioning of lungs. Automatic diagnosis system in medical imagining has increased the survival rate of lung patients at early stage from 20 percent to 70 percent based on 5 years survey since it provides the appropriate results at the right time. (Gajdhane & Deshpande, 2014). The survival rate prediction is alarming and the necessary factor which proved to help in proper treatment and diagnosis of lung cancer patient (Hawkins et

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al., 2014). There are two major types of lung carcinoma broadly subdivided into nonsmall cell lung cancer and small cell lung cancer. The nonsmall cell lung carcinomas subtypes are squamous cell carcinoma, adeno carcinoma and large cell carcinoma (Patil & Jain, 2014). The prognosis of lung Tumor is the most challenging task as the cells are assembled on each other therefore it is essential to determine the features and structure of diagnosed image (Tiwari, 2016). The automated lung nodule detection on medical images involves image enhancement, image segmentation and feature extraction to classify the stages of tumor so that proper planning of treatment could be accomplished on lung cancer patient (Tariq et al., 2013). The research in the field of medical imaging is rising especially in magnetic resonance imaging of lung tumor so that effective technique could be developed for evaluation of tremendous data. On the medical lung MRI (Magnetic Resonance Imaging) zoomed image, the foremost method implemented is image filtering to remove distortion and improve the quality of image. There are numerous ways to perform filtering on image by using methods such as thresholding, fast Fourier transform, morphological operation, median filter, Gaussian filter (Dimililer et al., 2017). The median filter is found to be effective technique in this paper to remove noise and distortion (Tun & Khaing, 2014). There is various image segmentation algorithm used in medical image research for analysis of cancer detection and finding the measurement of lung nodule detection (Norouzi et al., 2014). Based on the previous research the segmentation technique on MRI image is broadly classified into (a) Thresholding (b) Clustering (c) Region-Growing (d) Edge and Line oriented (e) Region splitting (Sharma et al., 2018). Although various distinct techniques are proposed by the researchers in literature still the various methodologies are proposed to meet the challenges of segmentation and providing better outcomes. This paper includes the Marker controlled watershed transform (Kanitkar et al., 2015) algorithm which provides better results than adaptive Otsu algorithm for detection of abnormalities (Prasad, 2013). The Marker controlled watershed algorithm (Abdillah et al., 2017) is improved technique for observing the structure of lungs whereas the adaptive thresholding is dynamic method to analyse the image. Watershed algorithm is efficient image processing tool based on mathematical morphology to recognize and envision cancer presence in lungs of patient as it relocates the cancer on pixels with high contrast (Janardhanan & Satishkumar, 2014). The feature extraction on region of interest is performed after image segmentation to obtain the geometrical and intensity based mathematical characteristic on Magnetic Resonance imaging using masking and binarization. The features such as Area, Perimeter, Standard deviation and Centroid provide the location and other analysis features of tumor (Tun & Soe, 2014). The classifier system in medical image research diagnosis provides the evaluation of data of patient disease and gradually providing better results to experts. SVM has become progressively prevailing supervised learning algorithm including classification, novelty detection and regression (Sweilam et al., 2010). The dataset used for training and testing in Support vector machine is selected from cancer institute for research. A finite training set is formulated using previously known decision parameters. It is supervised learning approach which enables the input and output mapping functions from labelled and categorized training dataset. On the basis of training, SVM classifies the categories (Low, Medium, high) of unknown data intelligently for testing purpose (Kaucha et al., 2017). The presented paper has developed the computer aided diagnosis and established the prediction model of SVM (Support vector machine) (Xiuhua et al., 2010) by evaluation of parameters such as accuracy, sensitivity and specification using true and false prediction. This proposed system is an integrated diagnostic system for lung cancer detection and classifies the tumor patient stages by constructing optimal classifier using SVM (Support vector machine classifier).

2. MATERIAL AND METHODS

In the proposed system, Lung tumor segmentation is designed using different image processing technique to segment the portion where nodules are present. The lung dataset images are acquired from cancer imaging archive (Cancer Imaging Archive, n.d.). The image dataset belongs to different part of lungs containing minute microscopic particles. The combination of overlapped cells or particle leads to formation of Tumor. The Magnetic Resonance imaging images have been taken in this research due to better quality and less distortion in comparison to X-ray images (Uzelaltinbulat & Ugur, 2017). The MRI images are obtained from cancer imaging archive for the evaluation of lung cancer diagnosis at an early stage. The preprocessing, Segmentation, feature extraction and classification are the simulated steps performed on tumor dataset. Magnetic Resonance imaging provides the detailed analysis of living tissue which helps in detecting the deformities such as cancer and injuries (Atkins & Mackiewich, 1998; Dogra et al., 2018).

The MRI zoomed images of 20 patients are taken from cancer imaging archive training and testing the model using Support vector machine. The pulmonary nodule of image varies from beginning stage to higher stage. The classification categories are predicted as analysis experimental results. There are 14 images in training dataset and 6 images in testing dataset.

2.1. Preprocessing

In image processing, smoothing is the technique to provide clarity of image by removing the noise and highlighting the image. There are broadly two categories of image enhancement process that is spatial domain and frequency domain. The smoothing filter applied in this research paper is median filter. Unnikrishnan et al. (2007) stated that the evaluation is made on the basis of median of window pixels surrounding the observed pixel to determine the result of processed pixels (Unnikrishnan et al., 2007). It is linear gaussian filtering whose performance is effective for salt and pepper noise, speckle noise (Katiyar & Singh, 2017).

2.2. Segmentation

Image segmentation is the process of representing the image for examining the pixels. Image segmentation is the process of partitioning of image into non-overlapping, integral regions which are identical in reference to some characteristics. There are various methods for segmentation which are used in medical image applications depending upon their modality and other factors (Pham et al., 2000; Vijh et al., 2020). In this paper Marker controlled watershed transform segmentation (Bhargavi et al., 2015) is implemented as efficient technique for determining the segmented nodule region of tumor for stage prediction. Image Segmentation of lung Magnetic Resonance image is demanding and challenging technique for evaluation of lung tumor due to irregularity in size, structure, location and shape affecting the adjustment of neighbour normal tissues (Menze et al., 2015).

The watershed transform process the topographic surface and performs computation of water ridge lines and catchment basins (Derivaux et al., 2010). The segmentation outcome is analysed by the location of watershed lines. This approach creates the watershed by labelling the data image. It is basically extracting the seed indication and generating gradient using marker location to apply watershed on image. The results contain the set of contours covering the entire image. The advanced algorithm is used in this paper overcoming the problem of over segmentation by performing additional marker operation using masking. This algorithm is helpful to locate the area where there is presence of tumor.

The steps performed in Marker controlled watershed transform are following:

1. Calculation of segmentation function using gradient magnitude.
2. Computation of foreground markers performing opening by reconstruction and closing by reconstruction.
3. Computation of background markers using thresholding opening closing by reconstruction.
4. Modification of segmentation function so that the function contains only minima at the background marker location and forehead marker location.
5. Computation of watershed transformation by applying it on modified segmentation function.

2.3. Feature Extraction

Feature extraction is performed through binarization and masking of the region. There are various features which are considered to determine the region of interest where the particles are present. Feature extraction is an important stage of algorithm because it discovers various geometrical and intensity related characteristic of particles so that treatment of patient could proceed accordingly (Dimililer et al., 2016). It provides detailed understanding of image. The factors calculated are shown in experimental results and are considered as shown below:

1. **Area:** It provides the actual number of pixels in segmented region of tumor or within the boundary.

Perimeter: It provides the summation of interconnected outlines of region pixels of binarized image. Mathematically:

$$P = \left|S_n S_1\right| + \sum_{i}^{n-1} S_i S_{i+1}$$

where {S…Sn} are the set of boundary points.

3. **Standard Deviation:** The standard deviation of Gaussian factor determines the neighbourhood of pixels where weighted summation occurs.

2.4. Support Vector Machine

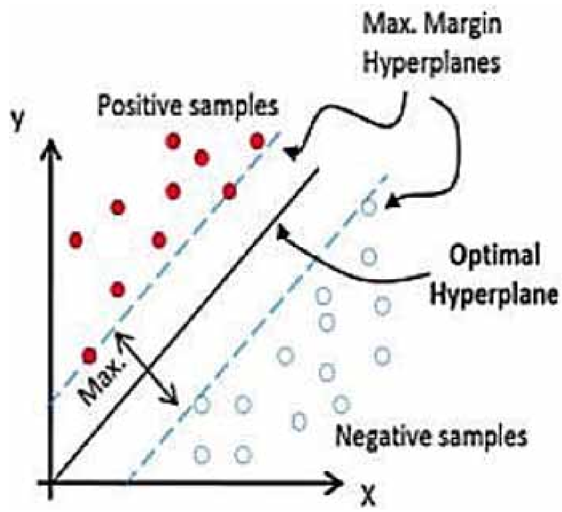
The SVM algorithm is developed by Vapnik and Lerner in 1963. Support vector machine uses the Multi class model learning technique to determine the prediction of different stages of lung tumor patient. SVM is considered as the most suitable technique to perform efficiently and accurately with high dimensionality feature spaces. The support vector referred to as subset of informative points is automatically identified by system (Ali & Feng, 2016; Vijh et al., 2019). SVM provides better results than other classifiers since it is two class classifiers. It is classified into two groups (a) Linear classifier (b) Nonlinear classifier. In Linear classifier, the training sample which are considered are linearly separable however in non-linear classifier the hyperplane is used for the separability of dataset (Machhale et al., 2015) (Figure 1).

SVM considers a linear function having hypothesis space in higher dimensional feature space which is instructed with a learning technique by employing a learning bias originated from statistical learning theory. SVM constructs optimal hyperplane and minimizes the risk of misclassification of dataset (Dwivedi et al., 2014). There are various forms of kernel function such as polynomial kernel function, Linear or Multi-layer perceptron kernel function, Radial basis kernel function. Every kernel function forms their own parameter. SVM is classification tool which evaluates the final summation with activation function to provide the final classification result (Sivakumar & Chandrasekar, 2013). Support vector machine is based on the idea of hyperplane which can maximize the margin between the classes. The MR images are trained so that multi spectral MR images can be classified and their stages of nodule can be detected on specification (Wang et al., 2008). The three different types of support vector kernel can be presented as:

1. Linear Kernel function L (x, z) = x, z;
2. Polynomial Kernel function L (x, z) = $\left(x \ \ , z+1\right)^p$ represents the degree of polynomial;
3. RBF L (x, x' = exp (-||x- x' ||/2 μ^2) where μ is positive real number and width of function.

The stages are categorized in Table 1.

Figure 1. Maximum - Margin Hyperplane



In Table 1, the nodule stage is classified into (a) Low (b) Medium (c) High. On the basis of research, the specification is considered such as for Low the tumor particle should be less than and equal to 3 cm, for medium the tumor particle should be greater than 3 cm and less than or equal to 7 cm, for high the tumor particle should be greater than 7cm.

2.4.1. Steps for Training

Step 1. Create the Training database for SVM classifier.
Step 2. Computing the iterator i=1.
Step 3. Assuming the class one and class two algorithm.
Step 4. SVM determines the maximum margin hyperplane to separate the classes.
Step 5. Updating the iterator.
Step 6. If condition satisfies that is if iterator is greater than N, than SVM generates the model file containing all N maximum margin plane.

2.4.2 Steps for Testing

Step 1. Create the testing database for SVM classifier (Table 2).
Step 2. Initialize iterator.
Step 3. SVM prediction model will read the image and validate it based upon training to predict the stage.
Step 4. Updating the iterator.
Step 5. If condition satisfies that is if iterator is greater than M, then it generates the prediction analysis.

Table 1. Stage of lung tumor

Intial Nodule Stage	Specification
LOW	Less than and equal to 3 cm
MEDIUM	Greater than 3cm and less than or equal to 7 cm
HIGH	Greater than 7cm

Table 2. Comparative analysis of related paper

References	Segmentation Technique/ Method	Classifier	Performance
Ada et al. (2013)	Histogram equalization	Artificial Neural Network	Accuracy- 90.04%
Preethi et al. (2016)	OTSU thresholding	-----	Detected Lung nodule
Asuntha et al. (2016)	Edge detection	Support vector Machine	Accuracy—89.5%
Kuo et al. (2017)	Texture feature enhancement method	Support vector Machine	Accuracy - 70.37%.
Vijaykumar et al. (2017)	Marker controlled watershed transform	Support vector Machine	Accuracy —70%
Kavitha et al. (2018)	Thresholding	SVM, ANN, KNN	Accuracy (%)—95%, 92%,85% Specificity (%)—88.24, 100.00, 76.47
Borzooie et al. (2018)	Density-based clustering algorithm, DBSCAN	N/A	Accuracy— 95.48%
Chiang et al. (2018)	CAD system based on 3D CNN and prioritized candidate aggregation	CNN	Sensitivity(%)—95%, 90%, 85%, 80%
Indira Priyadharsini et al. (2018)	Region growing technique	N/A	segmentation correctness — 91.2%

3. PROPOSED METHODOLOGY

The simulated flow of proposed algorithm for lung Tumor segmentation detection is shown in Figure 2. The techniques used are part of image processing and software used is MATLAB R2018a. The proposed methodology shown as follows:

1. Apply the Median filter on MRI (Magnetic Resonance imaging) image to reduce distortion and noise.
2. The Marker controlled watershed transform segmentation algorithm is implemented to evaluate the segmented region of pulmonary nodule tumor.
3. Calculation of features on region of interest. The features on basis of shape, size and location are considered such as area, perimeter, standard deviation and centroid.
4. Formulation of training and testing data for support vector machine learning task.
5. Formation of diagnosis rules for classification.
6. Classifying the Predicted analysis stage (Low, Medium and High) of pulmonary lung tumor nodule.

4. EXPERIMENTAL RESULTS

4.1. Simulated Results Analysis

The analysis of simulated process and their steps in obtaining the results are presented. The dataset consists of 20 images which are used for evaluation of nodule and predicting the accuracy, sensitivity and specificity. Depending upon the smoothing filter applied in this paper the following results are achieved in first stage as shown in Figure 3.

Figure 2. Lung tumor detection system using SVM

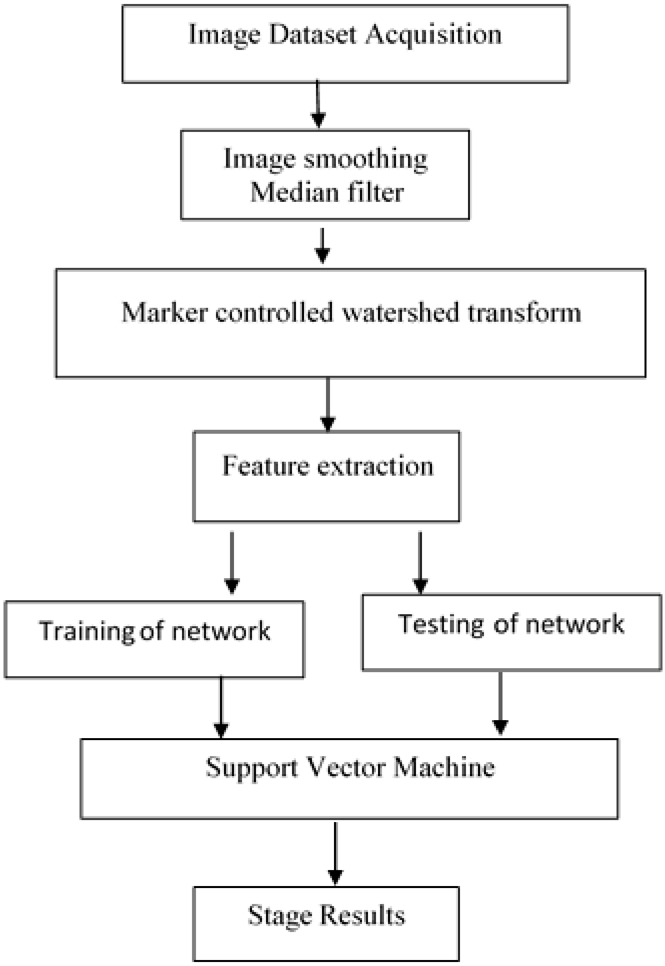
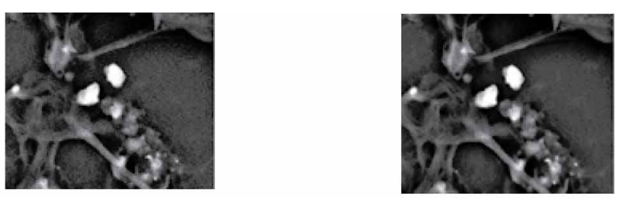


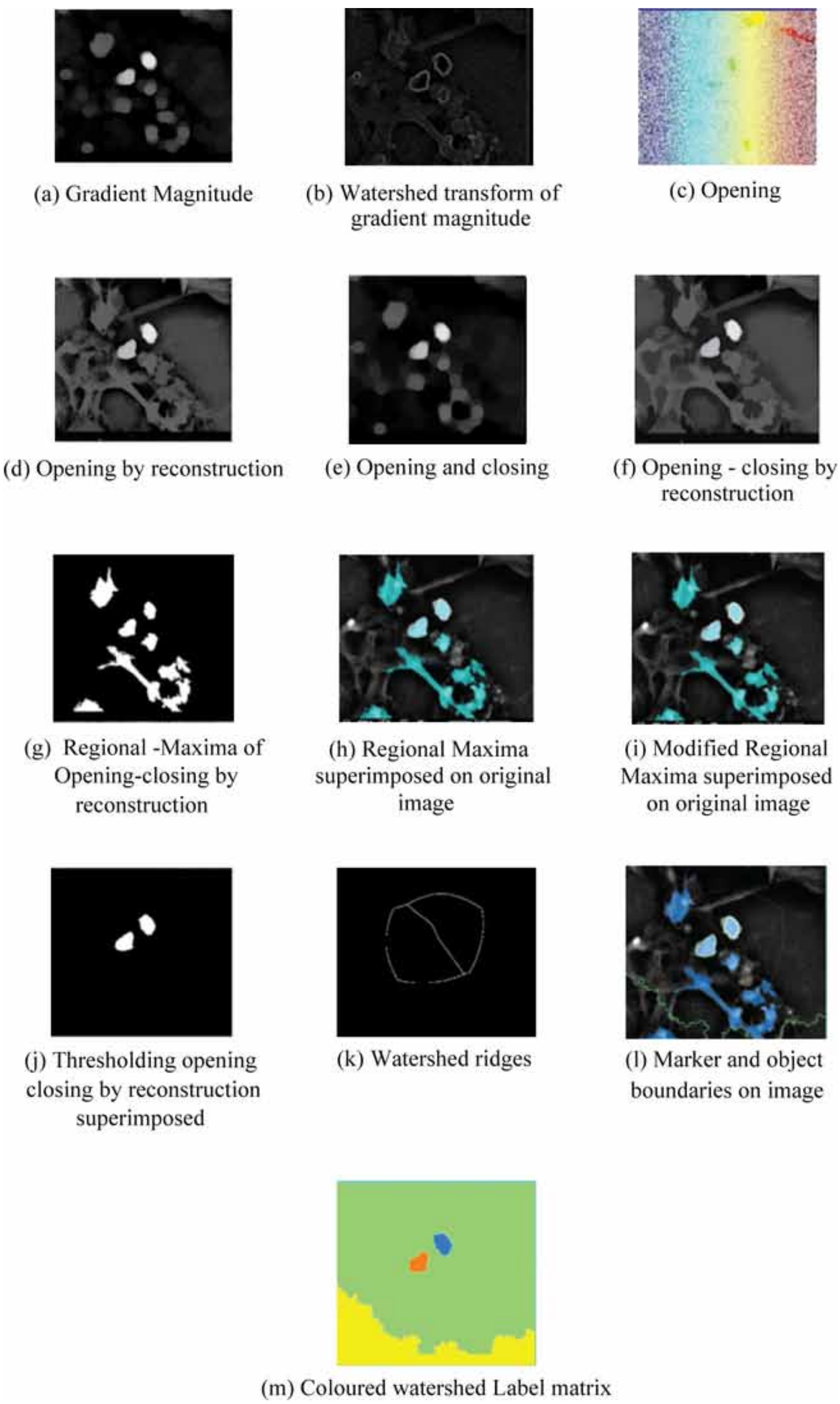
Figure 3. Filtered image



(a) Zoomed Original image (b) Filtered image

In step 2, the filtered image is given as input to Marker controlled watershed transform algorithm and following experimental results are achieved. The stages of outcomes achieved in series of steps are illustrated for the segmentation technique and it is observed that it is providing the better results for considered zoomed MRI image than any other segmentation technique (Figure 4).

Figure 4. Marker controlled watershed transform algorithm results



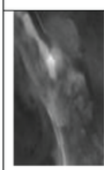
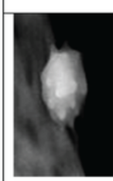
4.2. Parameters Calculation

See Table 3.

4.3. Performance Evaluation

The proposed system considers 20 lung tumor images which are segmented to detect the tumor and evaluate the different stages of lung tumor using support vector classifier. The 14 images belong

Table 3. Images with their corresponding values and Analysis results

Input image	Watershed Label image	Masking	Area	Perimeter	Standard deviation	Centroid at (x, y)	Analysis Prediction Result
			252	22	0.186	(366.4,346.2)	Medium
			167.63	61.4	0.446	(469.4,274.2)	Medium
			125.8	61.6	0.541	(395.7,430.1)	Low
			190.63	56.8	0.102	(405.4,368.2)	Medium
			318.5	67.4	0.175	(523,391.3)	High
			136.13	44.34	0.564	(546.3,343.7)	Medium

to trained network and 6 images belong to testing network purpose. The paper had considered area parameter to perform the classification. The performance evaluation is represented by the following considerations. The confusion matrix is computed on the basis of which the prediction is illustrated:

1. Accuracy is the total number of correctly classified stages of tumor detection for diagnosis:

Accuracy= [TP+TN/ Total] * 100

2. Sensitivity is the measure of true positives segmented image which are correctly classified stage:

Sensitivity= [TP/TP+FN] * 100
TP = overall number of correctly segmented image which are classified correctly
FN = overall number of correctly segmented image which are not classified correctly

3. Specificity is the measure of proportion of actual negative which is correctly identified:

Specificity = [1- FPR] * 100

FPR refers total number of incorrect segmentation and classified properly.

The training and testing performed is on basis of random 2/3 classification of images of lung tumor showing positive and negative outcome. The confusion matrix is computed for evaluating the different parameters such as accuracy, sensitivity and specificity. In presented Table 4, the accuracy of the segmentation and prediction of stage is obtained using support vector model and obtained as 92.86%. The sensitivity of the proposed algorithm and methodology is 95% and the specificity of the system is 100%. The outcome makes this algorithm efficient and effective for the future use.

Table 4. Performance evaluation

Estimated Results	Number of Images	Error Rate	Accuracy	Sensitivity	Specificity
Tumor	20	7.14	92.86%	95%	100%

5. RESULTS AND DISCUSSION

The proposed flow process of methodology is described in Figure 2 in which various technique used are presented. Figure 3 and Figure 4 shows the preprocessing and segmentation of image. It is observed that improved marker-controlled watershed segmentation technique provides better segmented region of tumored nodule. Table 3 presents the extracted features and their results analysis. The result analysis shows the stages of tumor. Table 4 contributes towards the performance evaluation and the outcome of proposed method. It shows that accuracy, sensitivity and specificity of 92.5%, 95% and 100% is achieved in proposed system. Figure 5 and Figure 6 presents the graphical representation of stage prediction and coding matrix.

6. CONCLUSION

Support vector classifier is a powerful tool for performing classification of lung tumor stage and determining the decision-making process. The proposed system designed the computer aided diagnosis

Figure 5. Stage prediction

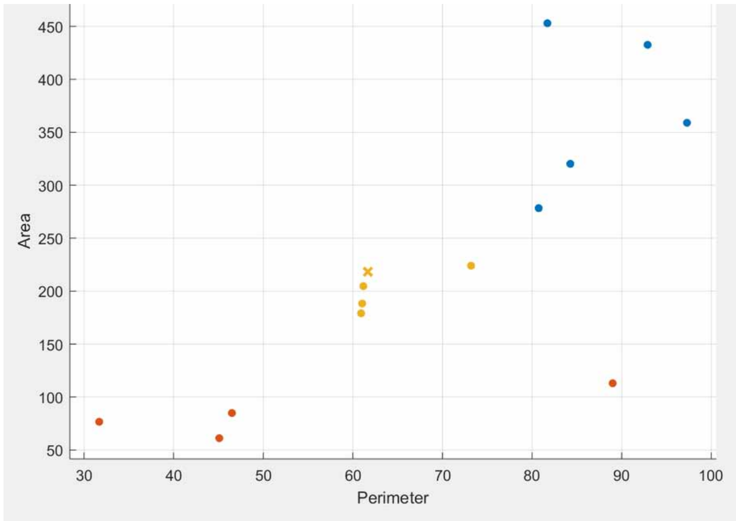
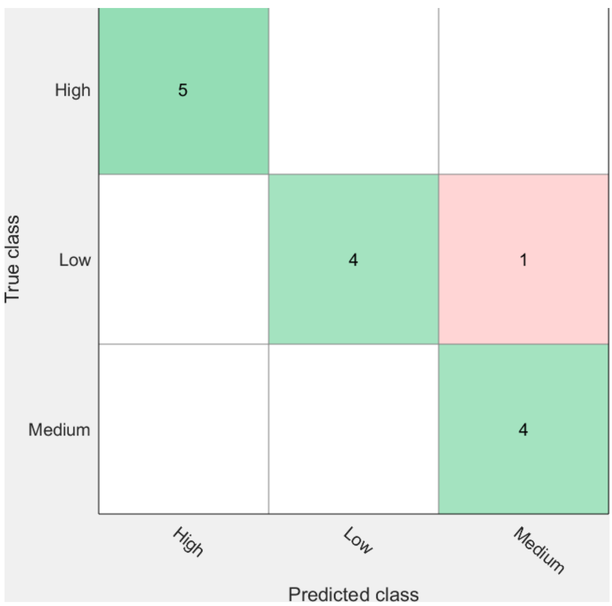


Figure 6. Coding Matrix



for lung tumor segmentation and classification. The study represents the early detection of lung tumor, determination of stages of lung tumor and process biopsy would be suggested by the physician if there is strong affirmation or evidence of lung cancer. The embedded model of segmentation and classification is achieved in this study with accuracy, sensitivity of 92.86% and 95% respectively using marker-controlled watershed algorithm and support vector machine. The simulated system provides feasible, efficient and accurate results over other system. In future we will be focusing on improving the accuracy by using some other classifier such as artificial neural network and metaheuristic techniques and improving the effectiveness of the system for different modality of lung tumor images.

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Surbhi Vijh is an assistant professor at KIET Group of Institutions.

Rituparna Sarma is an assistant professor at KIET Group of Institutions.

Sumit Kumar (PhD) is working as an associate professor in CSE Department at ASET, Amity University Noida. He has published 2SCI and 10 Scopus Index papers.