IMPLEMENTATION OF IMPROVED SEGMENTATION TECHNIQUE BASED ON IMAGE PROCESSING FOR DETECTION OF ORAL TUMOR

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ABSTRACT

Earlier Detection of cancer can save life. Image Processing plays a vital role in cancer detection. This paper discusses the use of Image Processing to detect and classify cancers from Dental X – Ray images. The current study proposed new segmentation algorithm namely Improved Marker Controlled Watershed Segmentation Algorithm (IMCWS). The proposed algorithm results in good accuracy and processing rate. Feature Extraction methods, Gray Level Co – occurrence Matrix (GLCM), Gray Level Run Length Matrix (GLRLM) and Intensity Histogram (IH) features are used to extract features from the segmented images. Later, classification between normal and abnormal cancer is made using Support Vector Machine (SVM).

Key words *- Gray Level Co – occurrence Matrix, Gray Level Run Length Matrix, Intensity Histogram, Improved Marker Controlled Watershed Segmentation and Support Vector Machine.*

I. INTRODUCTION

India is identified as one of the places with highest incidences of oral cancer and accounts for about 30% of all new cases annually [1]. The overall 5-year survival rate for all stages of oral cancer is 60%. These rates are better for localized tumors (82.8%) as compared to tumors with regional (51.8%) or distant metastases (27.8%) [2]. Survival rate can be improved by 80%, if oral cancers are detected in the earlier stage. While oral cancers unlike many other malignancies, can usually be seen with the naked eye. Some cancers are located internally in the body, making their detection difficult. Oral tumors can be diagnosed through Toluidine blue, Exfoliative cytology, Brush cytology, Light-based detection systems, Narrow emission fluorescence, Optical Biopsy, Optical Coherence Tomography, Gold Nanotechnology, Raman spectroscopy, Co - Axial Tomography, Barium Swallow, Positron Emission Tomography, Magnetic Resonance Imaging, Trimodal spectroscopy and Radiographs. Radiographs (also referred as X – Rays) assist in determining the growth of tumor in bones. Oral Cancers can be Benign, Premalignant or Malignant. According to [3], it is hard to distinguish Lichen Planus (non cancerous) from leukoplakia (precancerous lesion). Hence a diagnosis method is carried out by the oral surgeon from an intraoral image. According to WHO, Leukoplakia is defined as a predominantly white lesion of the oral mucosa that cannot be scraped off, and cannot be diagnosed as any other disease or definable lesion. The malignant transformation rate of oral leukoplakia varies from 0 to 33%. In the proposed system, X - Ray Images obtained are preprocessed using Linear Contrast stretching, and segmented using Marker Controlled Watershed Segmentation. As there are disadvantages with this

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segmentation, it is improved. After segmentation, features are extracted using GLCM, GLRLM and IH. Then using SVM classifier, classification is made to identify benign or malignant. The paper is organized as follows: Section II discusses about the literature work carried out in this field. In section III, methodology is shown. Results and Discussion are shown in Section IV. The work is concluded in Section V.

II. LITERATURE STUDY

Cyst and Tumor lesions are classified [4] using SVM on Dental Panoramic Images. Feature Extraction Techniques such as First Order Statistics, GLCM and GLRLM were used to extract features from ROI. Performance evaluation is 0.9278 for all the three methods.

Cyst and Tumor lesions from dental panoramic images [5] are classified using Active Contour Model. An average accuracy rate of 99.67% is obtained to show that segmentation with snake model can be used for cyst and tumor lesion on dental panoramic images. A method is proposed to detect and classify oral cancers using Data Mining [6]. Naive Bayesian and Support Vector Machine were implemented and compared the results to identify the best. The accuracy achieved using Naïve Bayesian method was 48.45%, while with SVM the accuracy obtained was 71.65%.

III. METHODOLOGY

The proposed work is carried out in various stages (Figure 1).

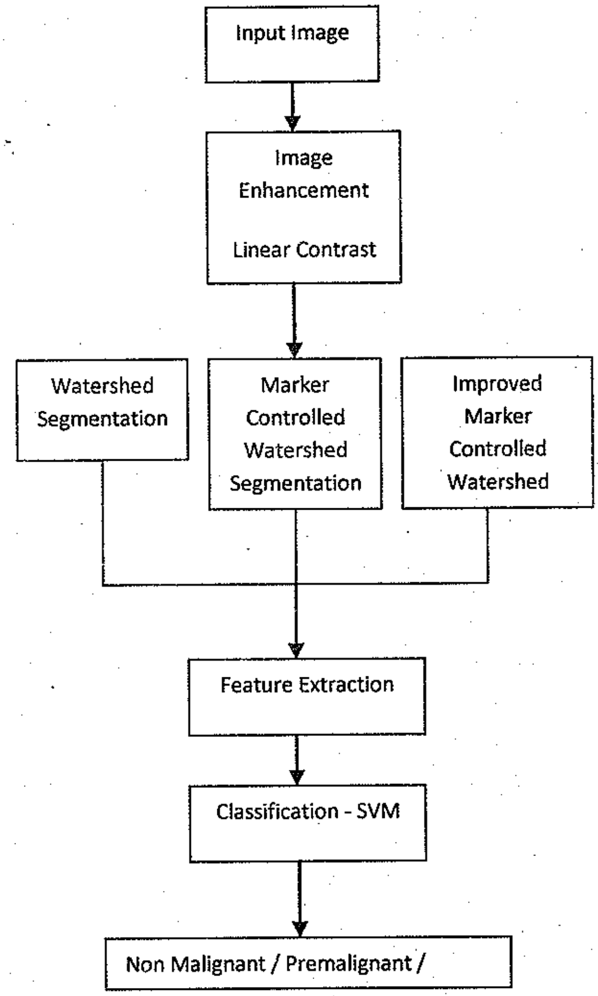


Figure 1 : Proposed System

A. Materials

A dataset of 50 dental X – Ray images including cyst lesions, tumor lesions and cancer lesions are taken for the proposed work.

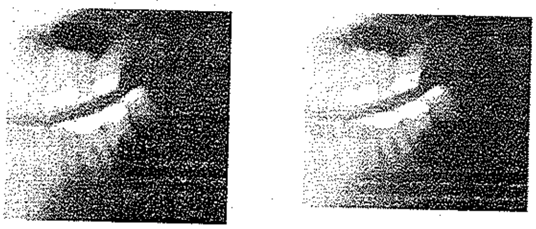
B. Image Preprocessing

The raw data obtained directly from X-ray Unit may yield a relatively poor image quality. An accurate segmentation is essential, but it becomes difficult due to low contrast and uneven exposure of the dental X – Ray images. Many researchers as referred in [7, 8] have proposed different techniques for contrast enhancement. Hence a proper enhancement technique is needed to remove noise from the image. In this work, Linear Contrast Stretching (LCS) is used to enhance the contrast of the image. Linear contrast enhancement, also referred to as a contrast stretching, linearly expands the original digital values of the remotely sensed data into a new distribution. While contrast is increased for a selected region, the teeth and bone regions become brighter and other regions including the tumor regions are clearly visible. By expanding the original input values of the image, the total range of sensitivity of the display device can be utilized.

The input images and the enhanced images are shown in Figures 2(a) to 2(d)

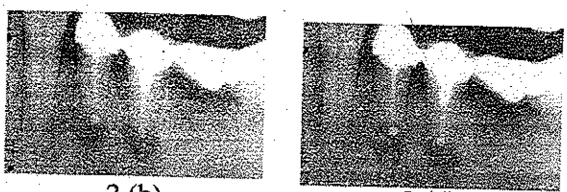
.C. Segmentation

The segmentation is the process of dividing images into regions according to their characteristics e.g., objects and color present in the images.



2 (a) 2 (c)

Figure 2 (a), (c) Input Image



2 (b) 2 (d)

Figure 2 (b), (d) Enhanced Image

These regions have some meaningful information about object and are sets of pixels. The results of segmentation are in the form of images that are more meaningful, easier to analyze and to understand. In order to locate boundaries and objects in images, feature extraction of texture, object shape, surface visualization, and optical density, image compression and image segmentation are used. Good segmented result is very useful for the predication, diagnoses and analysis.

In this work, initially watershed transform is applied to the preprocessed images. As watershed transform leads to over-segmentation,

Marker Controlled Watershed Segmentation is used. Due to its drawbacks, it is improved.

(i) Watershed Transform

The watershed transform [9] is a morphological based tool for image segmentation. Watershed Segmentations are applied for Figure 2 (c) and 2 (d). The segmented images (after Watershed Transform) are shown in Figure 3 (a) and 3(b) for figures 2(c) and 2(d) respectively.

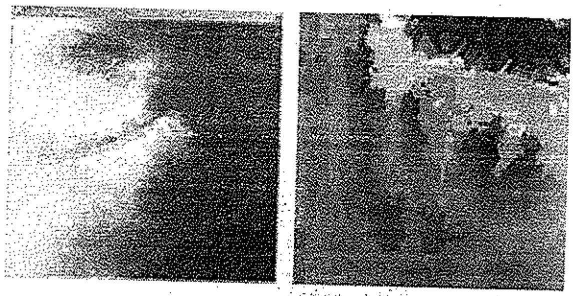


Figure 3 (a), (b) Watershed Transform

From Figure 3, it is clearly seen that the watershed segmentation is not complete and results in Over-segmentation. Hence Marker Controlled Watershed Segmentation is applied to Figure 2 (c) and (d).

(ii) Marker Controlled Watershed Segmentation (MCWS)

The segmentation using the watershed transform works better if we can identify, or mark, the foreground objects and the background locations, so Marker Controlled Watershed Segmentation follows this procedure [10]. The steps for MCWS are as follows:

1. Compute a segmentation function. This is an image whose dark regions are the objects to be segmented.
2. Compute foreground Markers. These are connected blobs of pixels within each of the objects.
3. Compute background Markers. These are pixels that are not part of any object.
4. Modify the segmentation function so that it only has minima at the foreground and background Marker locations.
5. Compute the watershed transform of the modified segmentation function.

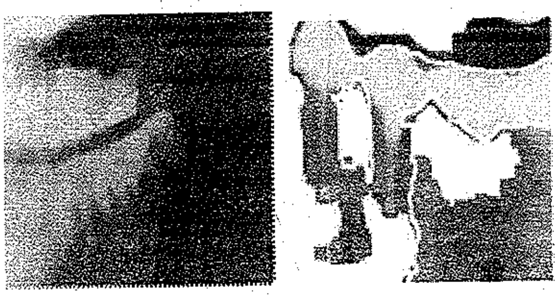


Figure 4 (a), (b) Marker Controlled Watershed Transform

Figure 4 (a) and (b) shows the results of MCWS for the images 2(c) and 2(d) respectively. But in Figure 4 (b), the segmentation is not complete. There is a sudden intensity change while segmenting the image. Thus MCWS cannot be applied for all images. So, it can be improved. Pixel's intensity is checked with its neighborhood pixels. The neighborhood pixels are plotted which are more or less same intensity level. The proposed algorithm (Improved Marker Controlled Watershed Segmentation) is applied for the enhanced image (Figure 2 d).

(iii) Improved Marker Controlled Segmentation

For some images, MCWS cannot be applied, so the same MCWS is improved for better segmentation.

The steps for Improved Marker Controlled Watershed Segmentation are:

1. Compute a segmentation function. This is an image whose dark regions are the objects to be segmented.
2. Compute foreground Markers. These are connected blobs of pixels within each of the objects.
3. Computer background Markers. These are pixels that are not part of any object.
4. Modify the segmentation function so that it only has minima at the foreground and background Marker locations.
5. Connect the points (pixels) of the same or relative intensity level (which reduces sudden change).
6. Compute the watershed transform of the modified segmentation function(Figure 5).The Advantage with this method is that it reduces the sudden change in the intensity level.

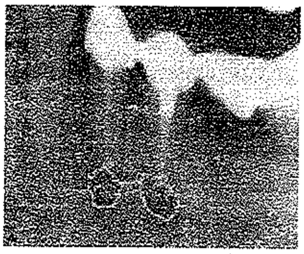


Figure 5 Output of Improved Marker Controlled Watershed Transform

From the segmented image (Figure 5), Features are extracted using GLCM, GLRLM and IH.

D. Feature Extraction

Transforming the input data into the set of features is called feature extraction. According to [11] there are three types of texture feature measures. They are:

- **First order** texture measures are statistically calculated from the original image values, like variance, and do not consider pixel neighbor relationships. Eg. Intensity Histogram and Intensity Features.
- **Second order** measures consider the relationship between groups of two (usually neighboring) pixels in the original image. Eg. GLCM
- **Third** and higher **order** textures (considering the relationships among three or more pixels) are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty. There has been some recent development of a more efficient way to calculate third-order textures:

In this paper, GLCM, GLRLM and IH are used to extract features from the segmented image. Totally 16 features are extracted using GLCM (5 features), GLRLM (7 features) and IH (4 features).

(i) Gray Level Co – occurrence Matrix

Statistical methods use second order statistics to model the relationships between pixels within the region by constructing Gray Level Co-occurrence Matrices [12]. A GLCM is a matrix where the number of rows and columns are equal to the number of gray levels, G, in the image. The features that are extracted using GLCM are: Energy, Contrast, Entropy, Correlation and Homogeneity.

(ii) Gray Level Run Length Matrix

A gray level run –length matrix (GLRLM) method is a way of extracting higher order statistical texture measures. A set of consecutive pixels with the same gray level, collinear in a given direction, constitute the gray level run. The run length is the number of pixels in the run and the run length value is the number of times such a run occurs in an image. The GLRLM is a two dimensional matrix in which each element $p(i, j\,|\theta)$ gives the total number of occurrences of runs of length "j" at gray level "i" in a given direction θ [13].

(iii) Intensity Histogram

Intensity Histogram features are extracted from the segmented image. The features that are extracted are Third Moment, Uniformity, Smoothness and Entropy. A frequently used approach for texture analysis is based on statistical properties of Intensity Histogram. A histogram is a statistical graph that allows the intensity distribution of the pixels of an image, i.e. the number of pixels for each luminous intensity, to be represented. By convention, a histogram represents the intensity level using X-coordinates going from the darkest (on the left) to lightest (on the right). Thus, the histogram of an image with 256 levels of grey will be represented by a graph having 256 values on the X-axis and the number of image pixels on the Y-axis. The histogram graph is constructed by counting the number of pixels at each intensity value.

E.Image Classification

The last step of the proposed system is classification. SVM classifier is used for classification.

(i) Support Vector Machine

Support Vector Machine (SVM) is a supervised learning model with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The original SVM algorithm was invented by Vladimir N. Vapnik and the current standard incarnation (soft margin) was proposed by Vapnik and Corinna Cortes in 1995. The basic SVM takes a set of input data and predicts, for each given input, the best of two possible classes forms the output. The classification process is divided into the training phase and the testing phase. The known data is given in the training phase and unknown data is given in the testing phase. The accuracy depends on the efficiency of classification.

IV. Experimental results

The proposed method has been implemented using .Net and MATLAB. In order to evaluate this work, experiments are conducted over 50 normal and cancer cases. Initially the segmentation algorithms are compared for speed and accuracy. From the segmented image, features are extracted using GLCM, GLRLM and IH. Later SVM classifier is used to classify the tumor as benign and malignant.

A. Speed Comparison

In this section, the images are segmented using Watershed, Marker Controlled Watershed Segmentation and Improved Marker Controlled Watershed Segmentation algorithms (shown in Figure 3, 4 and 5). A comparison is made to analyze these algorithms which take less time to segment the image.

Speed is calculated using,

Speed = (100 – (I – F) / 60) in seconds———————1

where,

I is the initial input time (0.0 seconds) and

F is the Final process time (in seconds).

And Accuracy can be calculated using the relationship,

Accuracy = (No. of records classified correctly/

Total Records) x 100 ——————————2

Table 1. Comparison of Segmentation Algorithms

Segmentation Algorithm	Accuracy	Speed (Without Stretching)	Speed (after LCS)
Watershed Segmentation	85.20%	87%	91%
Marker Controlled Watershed Segmentation	96%	90%	92.55%
Improved Marker Controlled Watershed Segmentation (proposed)	98%	90.5%	92.6%

To compare speed, 10 cases are considered and tested. From Table 1, the speed of segmentation algorithms after

Linear Contrast Stretching are 91%, 92.55% and 92.6% for Watershed segmentation, Marker Controlled Segmentation and Improved Marker Controlled Watershed Segmentation respectively. So, the Improved Marker Controlled Segmentation algorithm has less time to segment the image compared to the other segmentation algorithms.

B. Feature Extraction

Five GLCM features, Seven GLRLM features and Four Intensity Histogram features are extracted from the segmented image [14]. The features extracted are shown in Table 2, 3 and 4. These features are fed in SVM classifier.

C. Performance Evaluation

A confusion matrix provides information about the actual and predicted cases [15]. The performance of the prediction is evaluated in terms of sensitivity, specificity and accuracy. The formulae are given in Table 5.

Accuracy measures the quality of the classification. It takes into account true and false positives and

negatives. Accuracy is generally regarded with balanced measure whereas sensitivity deals with only positive cases and specificity deals with only negative cases.

Table 2. GLCM Features

Feature	Img1 (normal)	Img2 (normal)	Img3 (cancer)	Img4 (cancer)	Img5 (cancer)	Img6 (normal)	Img7 (cancer)	Img8 (normal)	Img9 (pre)	Img10 (pre)
Energy	0.1453	0.1961	0.5936	0.7214	0.6734	0.1543	0.5568	0.1876	0.4562	0.3997
Contrast	0.1904	0.2661	0.7269	0.8175	0.7563	0.2673	0.7754	0.1899	0.6122	0.6732
Entropy	4.9486	5.0543	6.9135	7.4569	6.7845	4.8734	6.9065	4.9996	5.8654	5.5903
Correlation	2.2454	2.5357	3.9767	4.1253	4.2781	2.4532	4.9067	2.8965	2.9056	2.8965
Homogeneity	1.1227	1.2647	1.9835	2.0626	1.9067	1.1674	2.0543	1.2654	1.7841	1.6903

Table 3 GLRLM Features

Features	Img1 (normal)	Img2 (normal)	Img3 (cancer)	Img4 (cancer)	Img5 (cancer)	Img6 (normal)	Img7 (cancer)	Img8 (normal)	Img9 (pre)	Img10 (pre)
SRE	0.1256	0.1345	0.3926	0.8086	0.6783	0.1987	0.7654	0.1342	0.2761	0.2453
LRE	0.1351	0.0903	0.3926	49.8872	39.0945	0.1399	47.889	0.0953	0.2678	0.2894
GLN	498.1120	435.3892	772.9222	893.68	759.456	422.3483	765.456	432.6743	590.654	579.0567
RP	0.0433	0.0854	0.2556	33.8906	10.9875	0.0634	15.8976	0.0934	7.8945	7.9034
RLN	298.2194	254.9001	726.8577	758.12	634.654	278.6122	657.453	245.6529	456.8342	433.9033
LGRE	0.0213	0.0256	0.0613	0.1157	0.1674	0.02674	0.1452	0.0287	503.3492	510.8904
HGRE	8.5462	9.1345	33.6910	70.6917	78.8956	9.1256	75.5643	8.3417	36.7819	39.8975

Table 4. Intensity Histogram Features

Features	Img1 (normal)	Img2 (normal)	Img3 (cancer)	Img4 (cancer)	Img5 (cancer)	Img6 (normal)	Img7 (cancer)	Img8 (normal)	Img9 (pre)	Img10 (pre)
Third Moment	0.0561	0.0532	0.2138	0.3621	0.2954	0.0487	0.4121	0.0345	0.1382	0.1293
Uniformity	0.1245	0.1845	0.4612	0.4932	0.4238	0.1634	0.4723	0.1723	0.2713	0.2654
Smoothness	0.5623	0.529	0.9315	1.0934	1.0453	0.5323	1.0834	0.5003	0.9543	0.8563
Entropy	4.9467	5.0563	6.9349	7.4544	6.9812	4.8734	7.0903	4.8936	5.1659	5.6126

Table 5. Formula for Measures

Measures	Formula
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)
Accuracy	(TP+TN)/(TP+FP+TN+FN)

Here, TP is number of true positives, FP is number of false positives, TN is number of true negatives and FN is number of false negatives. A confusion matrix (referred in Table 6) provides information about actual and predicted cases produced by classification system. The performance of the system is examined by demonstrating correct and incorrect patterns.

Table 6.Confusion Matrix

Actual	Predicted	
	Positive	Negative
Positive	TP	FP
Negative	FN	TN

TP-predicts cancer as cancer, FP-predicts cancer as normal, TN-predicts normal as normal, and FN- predicts normal as cancer. From [14], the feature extraction values are obtained using Marker Controlled Watershed Segmentation. It is observed that the accuracy TP is number of true positives, FP is number of false positives, TN is number of true

calculated from [14] are 88%, 96% and 92% using Intensity Histogram, GLCM and GLRLM. Now, with, Improved Marker Controlled Watershed Segmentation (IMCWS), the new values are calculated and are shown in Table 7.

Table 7. Matrix for all three Techniques

Value	IMCWS + Intensity Histogram	IMCWS + GLCM	IMCWS + GLRLM
TP	24	24	24
FP	2	0	1
FN	3	1	2
TN	21	25	23

From the values obtained in Table 7, Accuracy, Specificity, Sensitivity are calculated using the Formula given in Table 5.

Table 8. Performance Measures

Measure	Intensity Histogram	GLCM	GLRLM
AC	90%	98%	94%
SN	89%	96%	92%
SP	91%	100%	96%

From Table 8, it is observed that the accuracy obtained for GLCM, IH and GLRLM are 98%, 90% and 94%. The better performance is seen in GLCM. Hence GLCM is the best Feature Extraction Technique. The comparison of Segmentation algorithms and Feature Extraction Techniques are shown in Table 9.

Table 9. Comparison of Algorithms

Method	AC	SN	SP
MCWS + GLCM	96%	92.71%	100%
IMCWS + GLCM	98%	96%	100%
MCWS + IH	88%	85%	90%
IMCWS + IH	90%	89%	91%
MCWS + GLRLM	92%	88%	95.45%
IMCWS + GLRLM	94%	92%	96%

V. Conclusion

In this work, the images are captured and the series of operations are performed to identify the classification as normal or abnormal. The tumor is segmented using Marker Controlled Watershed segmentation and Improved Marker

Controlled Watershed Segmentation. The features are extracted using GLCM, GLRLM and Intensity Histogram. Further SVM classifier is used for classification. Accuracy obtained for GLCM feature extraction is 98%. GLCM gives a better performance when compared with other techniques.

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