

# Improved Technique to Diagnose Skin Cancer using Advanced Image Processing and Machine Learning Techniques

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**Abstract:** Skin cancer is being classified among the mortal and exaggerating forms of cancer since decade. Notwithstanding, the early diagnosis of skin cancer is very important and it is an extravagant procedure. The presence of human skin is tough to examine and to model. This is because of its complex surface. The difficulty of the irregular edge, tone, appearance of thick hair and other alleviating features generate the skin tough to be analyzed. Human skin has some non-identical sorts of textures that diseased skin can characterize between the textures of the healthy one. In consequence, considerable achievements have not been brought into the evolution of diagnosis approach for skin cancer. On the other hand, skin cancer diagnosis in dermoscopic portrayals is an exceptionally troublesome chore. Notwithstanding, the early diagnosis of skin cancer is very important and it is an extravagant procedure. In consequence, considerable achievements have not been brought into the evolution of diagnosis approach for skin cancer. For precise diagnosis and categorization of skin cancer, particular features are recommended that one may categorize benign and malignant illustration. A midst analysts, governing the efficacious mechanism of skin cancer diagnosis is an all-important matter of contention. Ascertaining the more proficient methods of diagnosis to minimize the amount of errors is a crucial subject among analysts. Image processing is used to recognize the affected area by disease, its form and color etc. The reason behind it is to minimize the percentage of miscalculations. Computer vision can bring about influential contribution in skin cancer detection. Computer Aided Diagnosis provides support in the premature diagnosis of skin cancer. Programmed skin abrasion segregation is a stimulating chore because of the low contrast between abrasion and encompassing skin and asymmetrical periphery. In this paper we present an amalgamation of statistical features, GLCM features and GLRLM features. The recommended methodology is enacted on 100 images from PH2 database. In this work 2 segmentation tactics namely Otsu's thresholding and Region growing have been explored. The performance of two systems is measured in terms of sensitivity, specificity, accuracy, precision, recall and f-measure

**Index Terms:** Biomedical image processing, Skin cancer, Gray-level Co-occurrence Matrix, Grey-level Run Length Matrix, Region Growing, Otsu thresholding, supervised classification

## I. INTRODUCTION

Skin that accounts for 4-5 kg mass and surface area of about  $1.2 \text{ m}^2$  -  $2.2 \text{ m}^2$  is an eminent and gigantic organ of human. The very organ safeguards the body from outer environment. It overhauls the temperature of body and entitles

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human to perceive sensations. Bearings that obstruct, modify skin appearance or deteriorate the skin can induce traits like inflammation, redness and rawness. Hypersensitivity, annoyance, and specific diseases can create diverse skin problems. But the most menacing disease, the skin can breed is cancer. Skin cancer is the utmost frequent and widespread sort of cancer that elucidates about 3.5 million cases. It is fatal if not diagnosed prematurely. Skin cancer can be tabulated as benign and the malignant. The malignant one is mortal form of cancer and in such a way it necessitates instantaneous diagnosis. It emerges from cancerous extension in pigmented abrasion. Meanwhile, benign skin abrasion is a usual skin and not menacing like malignant skin abrasion. Diagnosis of skin cancer is henceforth an important chore. Various methodologies have been implemented as of now to categorize the skin abrasion. The ABCD rule is by far considered as foremost dermoscopy innovation for the diagnosis of skin cancer [1],[2]. Neural network is considered as the efficient approach for classification purpose [3]. Amongst classifiers, the support vector machine(SVM) and k-means clustering can significantly perform well for classification or regression issues [4]-[5]. In the latest research, analysts employ snake's algorithm for optimum results [6]. Nevertheless untimely diagnosis of skin cancer is a complex job. Initially, the cast intra-class diversification of skin cancer concerning colour, appearance, form, magnitude in dermoscopy portrayals and resemblance among benign and malignant make it hard to differentiate malignant from non-malignant ones. Second, the respective low variation and hazy peripheries among skin abrasions and usual skin part make the programmed diagnosis function even complicated. Last, the appearance of clamour may un-focus the abrasions [7]. Numerous attempts have been devoted on resolving this complication. Premature evaluation aims to affect features to discriminate skin cancer from normal skin comprising colour [8], [9], texture [10] or both [11], [12]. Malignant melanoma cases have been notably exacerbating in decades, making it one of the tumours that has been experiencing consideration from medical management and tumour analysis domain. While numerous fresh instances of skin cancer are being detected every year, a programmed methodology to support the avoidance and premature diagnosis is distinctly desirable. With a view to refine the diagnostic pursuance of skin cancer, dermoscopy methodology was established. Dermoscopy is an approach that is utilized by dermatologists to detect skin cancer at the present time. The medical practitioner settles the gel on the abrasion and monitors it with an amplification tool that expands the abrasion. This expansion entitles the detection of specific surface



that is out of sight to naked eye. This can then be employed to detect an abrasion utilizing specific symptomatic algorithms like ABCD rule [1], [13], menzies method, seven point checklist having alike initial step, that is, discerning the abrasion with reference to its emergence as melanocytic or non-melanocytic. Dermoscopy can literally intensify the vulnerability of melanoma diagnosis by 10-27%, only if practitioner has endured official guidance.

The detection of abrasion by medical practitioner is nevertheless instinctive as it is build upon human observation. Thus programmed dermoscopy image evaluation can be employed to pursue this difficulty. In this type of methodologies, a computer is employed as a diagnostic appliance to investigate doubtful abrasions. Automatically fragmenting the melanoma from adjoining skin is an indispensable step in programmed or automated interpretation of dermoscopic portrayals. The identical perspective for prematurely diagnosing skin cancer comprises divergent steps of pre-refining, subdivision, feature withdrawn and categorisation. The outcomes of each step pay vital contribution to avert misdiagnosis. A review on procedures and steps of CAD system on melanoma has been provided by [14]. Whilst the accomplishment of CAD methodologies relies upon Pre-refining, the foremost level of CAD methodology has solemnly consequences on misleading the outcomes. A contrast of various pre-refining approaches has been illustrated in [15]. Some analysts offered to engage feature selection algorithms and the amalgamation of features [16]. Few analysts offered to accomplish segmentation [17] and on the basis of this, classify the melanoma as benign and malignant. The latest research reveals that the smart phone application can be much beneficial for the diagnosis of skin cancer [18]. From literature, it may be noticed that an improved algorithm, in order to segment the skin abrasion is a prerequisite task. Also the literature reveals the use of statistical, structural and textural features. The propounded features lack on the subject of robustness and therefore the introduction of robust feature set is an essential condition. In order to reduce the complexity of categorization of various algorithms, the reduced feature set is a prerequisite. The contrast among different classifiers is required to be explored that one may be able to select the appropriate one. The comparison of various classifiers with reference to their accuracy and other performance metrics need to be developed.

In this paper the contrast amidst segmentation approaches for skin cancer diagnosis has been carried out. The first methodology uses the otsu's segmentation that automatically implements clustering-based image thresholding. It reduces gray scale image into a binary one. Otsu's methodology recapitulates uninterruptedly to every feasible threshold values, computing a measure of stretch for pixel magnitudes on adjoining side of threshold. This methodology picks the threshold to reduce the intra-class variation of threshold among the pixels. The second system uses region-growing methodology that explores adjoining pixels of preliminary seed points. It regulates whether or not the adjoining pixels should be attached to the region and the mechanism is recapitulated on. The major objective of this technique is to divide an image into regions. This segmentation governs the region precisely. This paper attempts to discover contrast amongst the two approaches and implement the results in skin

cancer detection.

## II. PROPOSED METHODOLOGY

The variation in skin abrasion as malignant and non-malignant makes it inconvenient to diagnose the skin cancer. Moreover, the skin cancer is evolving haphazardly thus determining the optimum descriptor to separate benign and malignant skin cancer is a vital function. In this paper, we introduce a set of particular features acquired from distinct descriptors in order to spot among benign and malignant abrasions. The elaborated flowchart of the recommended feature extraction and its fusion procedure is encapsulated in fig.1.

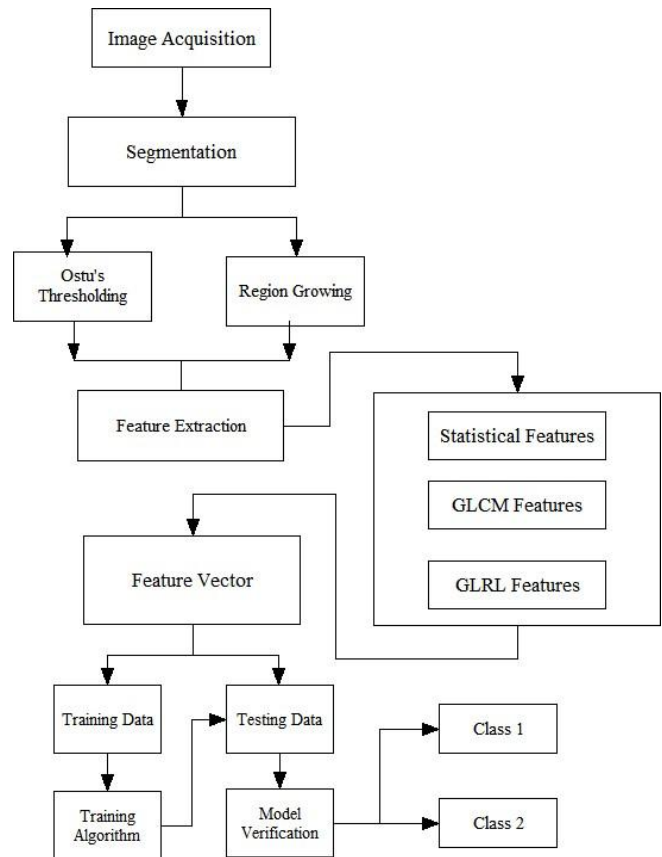


Fig.1 Flowchart of Proposed Methodology

### A. Dataset

The images have been acquired from the PH2 database [19]. A total of 100 images have been considered for the analysis.

### B. Pre-image Processing

Pre-refining is an eminent practice of designating benign and malignant skin cancer. Pre-refining comprises converting the image into a meaningful form. The statistics might be uncertain, partial or might also comprise error. The method is required to evacuate clamor that causes uncertainty to the classifier. The dermoscopic portrayals are 8 bit RGB images. The portrayals of the abrasion are transformed into grey scale form.

### C. Segmentation



Segmentation is an approach of segregating digital portrayals into segments that measure related characteristics to facilitate the characterization and creating it better for the investigation and explanation. Image segmentation is a requisite part of image evaluation procedure. The methodology discriminates among the entity to be examined and the alternative entities. The paper uses otsu's thresholding [20] and the region-growing technique for segmentation [21]. Fig. 2 shows the segmented sample images from both the methods.

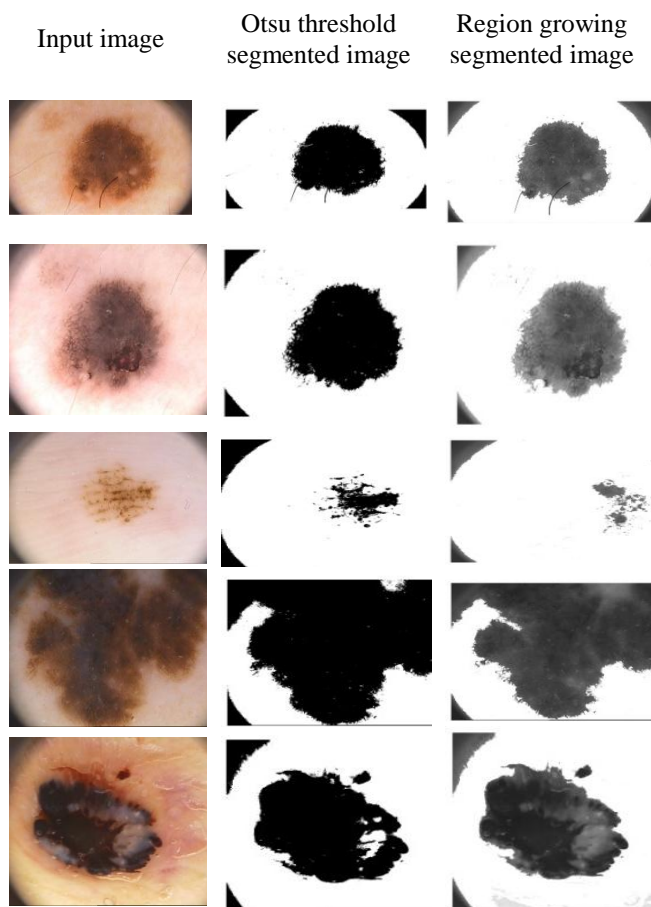


Fig.2 Input images versus otsu threshold segmented and region growing segmented images

#### D. Feature Extraction

The subsequent step is the extraction of features of the respective portrayals for the successive classification.

Features simply define the data extricated from images in numeral form and that can't be analyzed by human being. Features are distinctive signatures of particular portrayal. In this paper, GLCM Features, GLRLM Features and the statistical features have been extracted.

#### GLCM Features

GLCM or gray-level spatial dependence matrix has demonstrated to be a prominent statistical approach of withdrawing features from the portrayals. A co-occurrence allocation is a matrix specifically defined above a representation to be the distribution of co-occurring grayscale standards by a prearranged offset. Graycomatrix utility is

made use of to generate GLCM by estimating how frequently a pixel amid intensity value  $i$  come about in an explicit spatial connection to pixel amid value  $j$ . Every factor  $(i, j)$  in the resultant GLCM is basically the summation of the amount of times the pixel through value  $i$  transpired in a particular spatial connection to a pixel amid value  $j$  in the input figure [18]. GLCM extricates second order dermographic textural features named as: Autocorrelation, Cluster Entropy prominence, Cluster shade, Contrast, Correlation, Difference entropy, Difference variance, Dissimilarity, Energy, Homogeneity, Information measure of correlation 1, Information measure of correlation 2, Inverse difference, Maximum probability, Sum average, Sum entropy, Sum of squares variance, Sum variance.

#### GLRLM Features

GLRLM is the set of running pixels with the identical grey level  $i$  and run length  $j$  for given direction. Grey level run length matrix is evaluated that one may withdraw textural features. The following GLRLM features have been extricated in this research (Table I):

Table 1 GLRLM Feature set with mathematical formulas

SRE quantifies the allocation of short runs and higher rate of it designates well textures. LRE quantifies the allocation of long runs. Higher rate of LRE designates coarse textures. GLN quantifies the allocation of runs above the gray values. RLN quantifies the allocation of runs over run-lengths whereas RP quantifies the division of quantity of recognized runs.

**Statistical Features**

The method identifies the texture laterally[22]. Statistical method is employed that one may examine the dimensional spread of grey value by enumerating features consistently in image and acquiring a set of data from spread of features [23-26]. Table II shows statistical features which have been extricated in this paper.

Feature Name	Mathematical Formula
Mean Intensity	$\frac{1}{N} \sum_{i=1}^N X(i)$
Contrast	$\sum_{i=0}^{G-1} n^2 \left\{ \sum_{j=0}^G (P(i,j)) \right\}$
Correlation	$\sum_r^M \sum_c^M \frac{(r - \mu)(c - \mu)P[r,c]}{\sigma^2}$
Standard Deviation	$\sqrt{\sum_{i=0}^{L-1} [(x_i - m)^2 * p(x_i)]}$
Entropy	$\sum_{i=0}^{L-1} (p(x_i) * \log_2 p(x_i))$
Histogram	Five different levels of Histogram

Table II Statistical Feature set with mathematical formulas

**E. Classification**

Six classification parameters of 20 different classifiers have been calculated and compared in this paper.

**III. PERFORMANCE ANALYSIS**

The estimation of propounded methodology is computed maneuvering 6 performance measures that are Sensitivity, Specificity, Accuracy, Precision, Recall and F-measure:

- Sensitivity= TP/TP+FN (1)
- Specificity= TN/TN+FP (2)
- Accuracy= TP+TN/TP+FN+TN+FP (3)
- Precision=TP/TP+FP (4)
- Recall=TP/TP+FN (5)
- F-measure=(2\*Precision\*Recall) / (Precision+Recall)(6)

**IV. RESULT AND DISCUSSION**

**A. Performance Analysis of Otsu Thresholding**

The performance of the classifiers is illustrated employing the table known as confusion matrix. The necessary terms related to the matrix may be stated as TP or True Positive, TN or True Negative, FP or False Positive and FN or False Negative. Figure 3 shows the accuracy of different classifiers for the segmented images by otsu thresholding method. Table III compared the segmentation Results obtained by otsu’s thresholding methodology.

Classifier	Sensitivity	Specificity	Accuracy	Precision	Recall	F-measure
Complex Tree	92.80%	75%	90%	95.12%	92.85%	93%
Medium Tree	92.80%	75%	90%	95.12%	92.85%	93%
Simple Tree	92.80%	75%	90%	95.12%	92.85%	93%
Linear SVM	91.50%	64.70%	87%	92.68%	91.56%	91.49%
Quadratic SVM	91.76%	73.30%	89%	95.12%	91.76%	92.95%
Cubic SVM	93.67%	61.90%	87%	90.24%	93.67%	91.47%
Fine Gaussian SVM	92.04%	91.66%	92%	98.78%	92.04%	94.90%
Medium Gaussian SVM	94.04%	81.25%	92%	96.34%	94.04%	94.98%
Coarse Gaussian SVM	82.82%	100%	83%	100%	82.82%	90.10%
Fine KNN	95.12%	77.77%	92%	95.12%	95.12%	95%
Medium KNN	95%	70%	90%	92.68%	95%	93.47%
Coarse KNN	82%	0/0	82%	100%	82%	90.10%
Cosine KNN	95%	70.00%	90%	92.68%	95%	93.47%
Cubic KNN	93.82%	68.42%	89%	92.68%	93.82%	92.49%
Weighted KNN	95.18%	82.35%	93%	96.34%	95.18%	95.49%
Boosted Trees	95.06%	73.68%	91%	93.90%	95.06%	93.98%
Bagged Trees	94.04%	81.25%	92%	96.34%	94.04%	94.98%
Subspace Discriminant	92.68%	66.66%	88%	92.68%	92.68%	92%
Subspace KNN	94.04%	81.25%	92%	96.34%	94.04%	94.98%
RUS Boosted Trees	97.36%	72.72%	90%	96.97%	97.36%	93.36%



Feature Name	Mathematical Formula
Short Run Emphasis(SRE)	$\frac{1}{H} \sum_i \sum_j \frac{GLRLM(i,j)}{j^2}$
Long Run Emphasis(LRE)	$\frac{1}{H} \sum_i \sum_j GLRLM(i,j) \cdot j^2$
Grey Level Non Uniformity(GLN)	$\frac{1}{H} \sum_i \left( \left( \sum_j GLRLM(i,j) \right)^2 \right)$
Run Percentage (RP)	$\frac{H}{\sum_i \sum_j (j \cdot GLRLM(i,j))}$
Run Length Non-Uniformity(RLN)	$\frac{1}{H} \sum_j \left( \left( \sum_i GLRLM(i,j) \right)^2 \right)$
Low Grey Level Run Emphasis(LGRE)	$\frac{1}{H} \sum_i \sum_j \frac{GLRLM(i,j)}{i^2}$
High Grey Level Run Emphasis(HGRE)	$\frac{1}{H} \sum_i \sum_j GLRLM(i,j) \cdot i^2$

Table III. Performance evaluations of sensitivity, specificity, accuracy, precision, recall and F-measure for various classifiers under the otsu's thresholding methodology

The table presents as to which classifier performs better. The results obtained by the table illustrates that from sensitivity point of view, RUS Boosted trees outperformed all other classifiers with 97.36%. The specificity of 100% is achieved by Coarse Gaussian SVM classifier. The accuracy of 93% by Weighted KNN, precision of 100% by Coarse KNN, recall of 97.36% by RUS Boosted Trees and F-measure of 95% was achieved by Fine KNN classifier. The table presents the examples of segmentation results obtained by applying Otsu's thresholding segmentation method to original images. Fig.3 comprises the illustration results that analyze how efficaciously the abrasions were segmented by the otsu's thresholding technique. The figure demonstrates the accuracy versus classifiers relationship. The evaluation of results achieved demonstrated that the otsu's thresholding method is effective in diagnosis of skin abrasion and extracting their outlines from PH2 dataset figures.

Figure 4 shows the examples of confusion matrices for the otsu threshold algorithm of some selective classifiers. Table 3 illustrates the performances achieved in the name of sensitivity, specificity, accuracy, precision, recall and F-measure for various classifiers under the otsu's thresholding methodology. In order to measure the performance of otsu thresholding 6 performance measures, namely sensitivity, specificity, accuracy, precision, recall and F-measure have been evaluated. Then performances are evaluated by making use of the equations described above in section 3. Table III shows that from the sensitivity point of view, the best result is achieved maneuvering RUS Boosted Trees with sensitivity of 97.36%. If we consider specificity metrics, the best result is carried out by the Coarse Gaussian SVM classifier with 100% value. Weighted KNN reveals the

best accuracy result with 93%. Considering precision performance metric, the best result is given by the Coarse Gaussian SVM classifier with the 100% result. With regard to

Classifier	Sensitivity	Specificity	Accuracy	Precision	Recall	F-measure
Complex Tree	86.20%	89.15%	83%	50%	66.66%	53.45%
Medium Tree	52.94%	89.15%	83%	50%	52.94%	53.45%
Simple Tree	60%	89.28%	84%	50%	56%	53%
Linear SVM	91.66%	92.04%	92%	61%	91.66%	73.03%
Quadratic SVM	76.92%	90.80%	89%	55.55%	76.92%	63.81%
Cubic SVM	62.50%	90.47%	86%	55.55%	62.50%	58.29%
Fine Gaussian SVM	0/0	82%	82%	0/0	0/0	0/0
Medium Gaussian SVM	80%	88.88%	88%	44.44%	80.00%	56.77%
Coarse Gaussian SVM	83.30%	86.17%	86%	27.77%	83.33%	40.74%
Fine KNN	84.60%	91.95%	91%	61.11%	84.60%	70.67%
Medium KNN	88.88%	89%	89%	44.44%	88.88%	58.66%
Coarse KNN	0/0	82%	82%	0/0	0/0	0/0
Cosine KNN	50%	88%	82%	44.44%	50.00%	22.68%
Cubic KNN	88.88%	89.01%	89%	44.44%	88.88%	58.66%
Weighted KNN	90%	90%	90%	50%	90.00%	64.28%
Boosted Trees	76.92%	90.80%	89%	55.55%	76.92%	64.51%
Bagged Trees	78.57%	91.86%	90%	61.11%	78.57%	68.46%
Subspace Discriminant	76.90%	90.80%	89%	55.55%	76.92%	63.81%
Subspace KNN	71.40%	90.69%	88%	55.55%	71.42%	61.98%
RUS Boosted Trees	66.66%	92.68%	88%	66.66%	66.66%	66%

recall metric, the best result is shown by RUS Boosted Tree with 97.36%. And best result for F-measure with 95.49% is given by the Weighted KNN classifier. The results have revealed that for Otsu thresholding Boosted tree, coarse gaussian SVM and Weighted KNN classifiers showing the best results.



**B. Performance analysis by Region growing**

Performance evaluation of region growing segmentation algorithm has been shown in figure 5, 6 and table 4. Table IV demonstrates the performances realized in the name of sensitivity, specificity, accuracy, precision, recall and F-measure for a variety of classifiers under the region growing tactic.

Table IV reports the performance evaluations for various classifiers for region growing segmentation technique maneuvering Sensitivity, Specificity, Accuracy, Precision, Recall and F-measure. According to above table, the best result in terms of sensitivity is achieved by Linear SVM classifier with 91.66%. If we consider in terms of specificity, the best result is given by the RUS Boosted Tree with 92.68%. In terms of accuracy, the Linear SVM provides best result with 92%. The RUS Boosted Tree gives best result with just 66.66% in terms of precision metrics. If only recall is

Table IV Performance evaluations of sensitivity, specificity, accuracy, precision, recall and F-measure for various classifiers under the region growing methodology

considered, the best result is given by Linear SVM with 91.66%. And in case, only F-measure is considered, the best result is provided again by Linear SVM. So, from this discussion it is clear that for region growing segmentation, Linear SVM shows best results. The comparison between table IV and table V show that the otsu thresholding segmentation technique shows better result than region growing in all aspects i.e., in terms of sensitivity, specificity, accuracy, recall, precision and F-measure.

**V. CONCLUSION**

Commencing the outcomes over, the associated conclusions can be determined employing neural system diagnosis of skin diseases. This is feasible and realizable all the way through extraction, division and classification methodology. This paper has compared two approaches namely otsu thresholding and region growing segmentation for the skin cancer diagnosis characterized by GLCM features, GLRLM features and the statistical features. Initially [27], the abrasion region is segmented using otsu thresholding and region growing segmentation. Later, the features are extracted in order to represent the abrasion region. And then the classification is performed maneuvering various classifiers. The two approaches were investigated using a database known as PH<sup>2</sup> dermoscopy data-set. The experiments are carried out on 100 dermoscopic portrayals. The system parameters i.e., sensitivity (SE), specificity (SP), accuracy, precision, recall and F-measure were tested employing various classifiers. The results reveal that the otsu threshold technique outperforms the region growing segmentation in all performance metrics.

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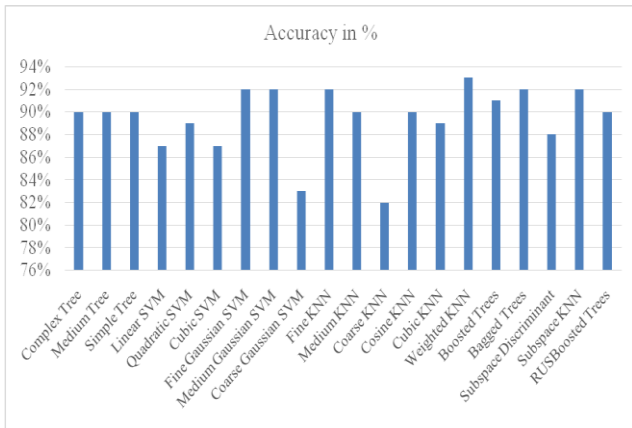


Fig. 3 Accuracy of different classifiers for the segmented images by otsu thresholding method

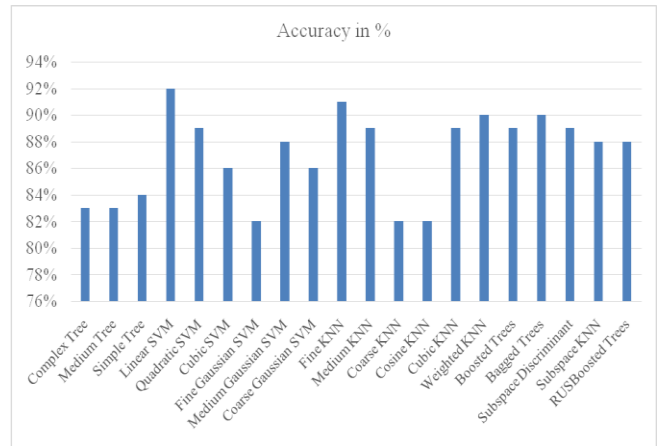


Fig. 5 Accuracy of different classifiers for the segmented images by region growing method

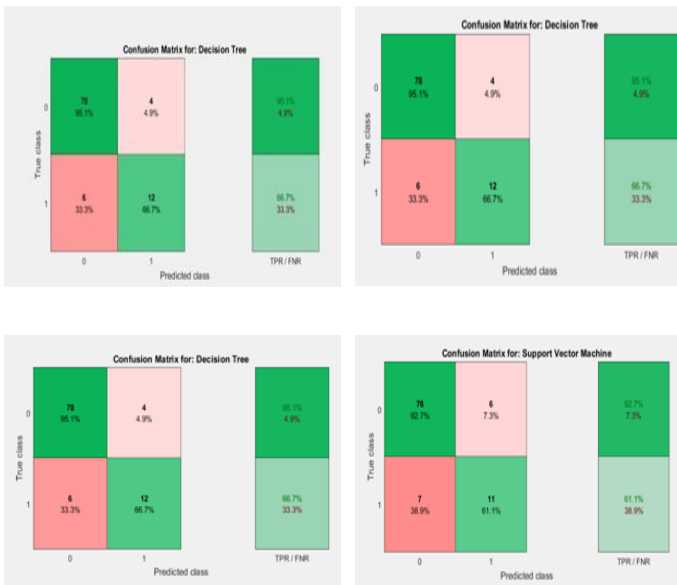


Fig. 4 Confusion matrices for the otsu threshold algorithm of some selective classifiers

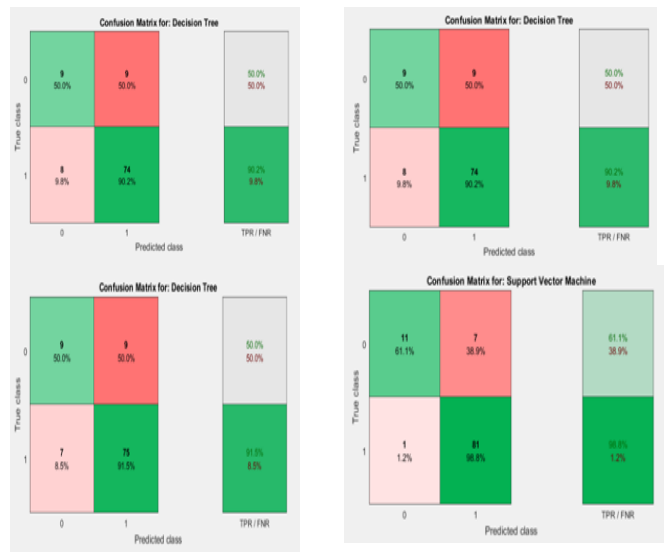


Fig. 6 Confusion matrices for the region growing algorithm of some selective classifiers