



THE MELANOMA SKIN CANCER DETECTION AND CLASSIFICATION USING IMAGE PROCESSING

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Abstract: The most common type of cancer is the skin cancer in human being. It can be benign and malignant. There are medical methods to detect it but that consumes more time. So, computer-based application needs to be developed to detect this disease in its early stages in order to augment the patient's survival likelihood. The aim of this paper to develop a simple and capable method to detect the melanoma. The proposed methods contain following stages, preprocessing, segmentation, feature extraction and classification. The accuracy of proposed method is 96.7% which shows its reliability.

Index Terms - Pre-Processing, segmentation, feature extraction, classification, image processing.

I. INTRODUCTION

Melanoma is the most harmful skin tumour found in the cell called melanocytes and they are on the upper layer of the skin. Melanocytes produces skin colour by producing pigment known as melanin. Melanin has its two different types first is eumelanin and second is pheomelanin. Eumelanin is a dark pigment (brown and black) where as Pheomelanin is a lighter pigment. The light skinned people has pheomelanin where a dark or dusky people has eumelanin. The main aim of eumelanin is to protect the skin from any sun damage and that is why dark-skinned people has less chances to get affected by the melanoma as compare to light skinned people.

Sunshine and tanning lamps and beds sensitivity to ultraviolet (UV) radiation is the exact cause of melanomas that mostly raise your risk for melanoma does help to growth. Limiter your vulnerability to UV radiation will help reduce your melanoma risk. Doctors diagnose melanoma by conducting a biopsy in which they detach, for examination, a piece of skin containing the pigmented tumour that is in its early stages and can be visible and sent to test in laboratory. This eventually develops deep into the skin and cannot be readily seen and affects other areas of the body too. If a doctor detects melanoma and treats it until it spreads, the average survival rate for 5 years is 98%. However, if it spreads to deeper tissues or neighboring lymph nodes, the risk drops to 64%. If it enters distant organs or tissues, the 5-year likelihood of survival drops to 23%.

A. Stages of Melanoma:

- The infection is only present in the outer edge of skin. Medical professionals find the stage to be "in situ melanoma."
- The infection has a thickness of up to 2 milli meters. Disease has not yet carried to lymph nodes or other areas, and may or may not become inflamed.
- The cancer has a thickness of at least 1 mm but can exceed 4 mm in length. This can be ulcerated or not, it has still not progressed to lymph nodes or any other locations.
- The tumour has spread to one or more or adjacent lymph nodes lymph channels but not far-off locations. The earlier cancer might not be noticeable any more. It may be denser than 4 mm if observable, and inflamed as well.
- The disease is spreading to nearby blood vessels or tissues, for e.g. the brain, lungs, or liver.

B. Symptoms:

- Any changes in the skin, like a newly generated mark or mole or changes in the shade, form or appearance of an existing patch or mole.
- Scab not curing.
- A spot or sore that is irritating, tender or itchy.

4. A bleeding spot, or sore.
5. A patch or chunk with a glossy, glassy, slick, translucent look.
6. A strong dark bleeding glob, or looks swollen or stinky.
7. A rough, dry, or hairless ground, red spot.

C. Prevention:

- a. In the middle of the day try not to get in contact with the sun. The sky gets the most rays at around 9 a.m. to 4:30 p.m. Plan outdoor events for other periods of the day, sometimes in winter or when the weather is dreary. You ingest UV radiation throughout the year and there is no safeguard against harmful rays in clouds.
- b. Apply protection cream year-round. Using a widescreen sun protection cream of at least 30 SPF, including on rainy days.
- c. Apply sunscreen gently, and keep applying every two hours or more regularly, if you swim or suck. Use safety robes. Protect the skin firmly, with dusk knit clothes.
- d. Minimize the use of tanning lamps and beds. Sun tan bulbs and beds emit UV rays, which can raise skin tumour threat. Get to know your skin and you'll find changes. Often check the skin for new growths of skin or improvements of present moles, red marks, and stretch marks. Check the face, arms, ears and scalp, using mirrors.
- e. Get to know your skin and you'll find changes. Often check the skin for new growths of skin or improvements of present moles, red marks, and stretch marks. Check the face, arms, ears and scalp, using mirrors.

D. Types of Melanoma:

- a) Actinic keratosis is a harsh, hairless patch that has been growing on your body for years of sun damage.
- b) Red moles, or angiomas of cherry, are normal skin growths that can occur in most areas of your body. They are also known as angiomas senile, or spots these may be skin cancer signs.
- c) One of the exceptions is Basal cell carcinoma, more annoying skin cancer than mortal foe. Basal cell skin cancer is the cancer that is most easily curable, and the least serious.
- d) Dermatofibroma (superficial benign fibrous histiocytoma) is a normal, unknown ethology cutaneous nodule that occurs more frequently in women. Dermatofibroma also occurs on the extremities (mostly the lower legs) and is typically asymptomatic although there may be pruritus and tenderness.
- e) One type is a melanocytic nevus (also known as nevocytic nevus) tumour. Estimates differ, but people with large melanocytic nevus are usually considered to have a lifetime chance of developing melanoma of 5 to 10 per cent. Melanoma normally begins in the nevus but can develop when melanocytes invade other tissues become cancerous, such as those in the brain and spinal cord.

II. PREVIOUS WORK

There are so many researchers who are working on skin tumour detection using computer-based approach [13]. To get the lesion part from the image many segmentation techniques have been used in different papers for instance, Otsu's threshold, Watershade Algorithm, K- means clustering, Canny Edge Detection and many more. The most common feature which has been used in many papers are texture, size, colour, shape and for the classification SVM, Decision Tree, MSVM, Naive Bayes Classifier, Neural Network are used. Below is the table that describe the summary of different techniques used in different papers for detecting the melanoma skin cancer.

Table 1. Related Work

Ref. no	Author	Kind of Class	Feature Extraction Approach	Classification Approach	Accuracy
[1]	N. Codella	Melanoma & Non-Melanoma	Convolutional Neural Network and Sparse Coding Features	SVM Classifier	93.10 %
[2]	Adria Romero Lopez ¹⁰	Melanoma & Non-Melanoma	Color histogram, edge histogram, and LBP	SVM	78.66 %
[3]	Germán Capdehourat	Melanoma & Non-Melanoma	Shape, color and texture features are extracted	Decision tree	85%
[4]	Rui FonsecaPinto	Melanoma & Non-Melanoma	Gabor filters, Wavelets and Curvelets transforms	AdaBoost Algorithm	96%
[5]	O. Abuzagheh	Benign, Atypical & Melanoma	2-D Fast Fourier Transform	SVM	96.3%
[6]	M.A. Sheha	Melanocytic Nevi & Malignant	GLCM	MLP	92%
[7]	A. Antony	Melanoma & Non-Melanoma	GLCM	ANN	86.6%
[8]	I. Immagulate	Melanoma & Non-Melanoma	Color and Texture	PSVM	93%
[9]	S. Thirumavalavan	Benign & Malignant Melanoma	Basic shape+ border irregularity + texture+ color	RBFN	86.36 %
[10]	R. Kasmī	Benign & Malignant	Asymmetry + Border+ Color	Tree decision	94%

From the various techniques that are mentioned in the above Table I it can be seen that the accuracy obtained is in between 78% to 96.3% but the images are classified into only two classes so the basic aim of the proposed work is try to enhance the accuracy. All these methods classify the image into cancerous and non-cancerous images only so the second aim of the work is classifying the images into six types of melanoma cancer.

III. METHODOLOGY

Table I shows accuracies obtained by combining different methods to detect the melanoma cancer and in this imaging system to increase the accuracy the combination of imfilter, Fuzzy C Means Clustering algorithm, GLCM, Gabor Filter and MSVM is been used and image is classified into six different classes. Methodology suggested to detect melanoma skin tumour is shown in following figure 1. The input for the imaging system is the image that has a doubt to have melanoma. The image is then pre-processed to enhance its quality. The Fuzzy C Means Clustering algorithm is been used to segment the affected area from the image. For extracting the features three feature extraction techniques has been combined they are GLCM and Gabor Filter. Classification is performed using Multi Class SVM.

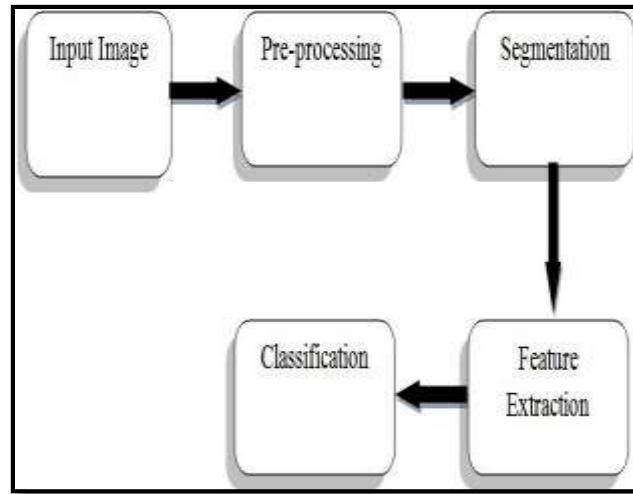


Fig. 1. System Design Flow

A. Pre-processing

The First ever step is to take the input image from the dataset and improve the quality of the input image which uses filter to contain unwanted noise.

- **Using imFilter filtration:** Images can be filtered, either by correlation or by convolution, using the imFilter toolbox function. It filters an image which contains a 5-by-5 filter with equal weights. A filter like that is also called an averaging filter. The function of the imfilter handles data types similar to how arithmetic functions of the image do. The output image has the same data type as the input image, or numeric form.

B. Segmentation

Segmentation can be used for automated detection of skin abnormalities and used to measure lesion properties such as shape asymmetry or border abnormalities that can help diagnose melanoma The Fuzzy C mean Clustering Algorithm is used for segmentation. Divided into two clusters of cancerous pixels, the foreground and the normal skin pixels as background.

- **FCM(Fuzzy C-Means Clustering) Algorithm:**

The method is an iterative clustering technique that creates an ideal c segment by limiting the weighted inside the gathering total of the squared error target work JFCM [5]:

$$J_{FCM} = \sum_{k=1}^n \sum_{i=1}^c (u_{ik})^q d^2(x_k, v_i) \dots \dots \dots (1)$$

where $X = \{x_1, x_2, \dots, x_n\} \subseteq R^p$ is the informational index in the p-dimensional vector space, n is the quantity of information things, c is the quantity of clusters with $2 \leq c < n$, u_{ik} is the level of participation of x_k in the i^{th} cluster, q is a weighting type on each fuzzy enrollment, v_i is the model of the center cluster i, $d^2(x_k, v_i)$ is a distance measure between object x_k and cluster center v_i . An answer of the function JF CM can be acquired by means of an iterative procedure.

C. Feature Extraction

After segmentation of the affected portion from the image, the image is labeled for extraction of some specific feature. The features that an image extracts are texture, shape, color, diameter. The filter GLCM and Gabor are used for extraction of the features.

- **GLCM (Gray-Level Co-Occurrence Matrix):**

The GLCM describe the texture of an image by measuring how many pairs of pixels with similar values occur in an image and in a given spatial relationship, generating a GLCM, and then extracting statistical measurements from that matrix. (The texture filter functions, as defined in Calculate Statistical Texture Steps, cannot provide shape information, that is, the spatial pixel relationships in the image). With gray comatrix, you can extract many statistics from these with graycoprops after you build the GLCMs. Such figures provide detail on an image's texture. The lists which follow describe the statistics.

- Homogeneity, Angular Second Moment (ASM):**

ASM is one indicator of an image's homogeneity. A homogeneous plot will contain just a few gray levels, giving only a few but relatively high P(i, j) values to a GLCM. The number of squares will thus be large:

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i, j)\}^2 \dots \dots \dots (2)$$

- Contrast:**

This way of measuring of contrast or variation of local magnitude will favor P(i, j) contributions away from the diagonal, i.e. $i \neq j$.

$$CONTRAST = \sum_{n=0}^{G-1} n^2 \{ \sum_{i=1}^G \sum_{j=1}^G P(i, j) \}, |i - j| = n \dots \dots \dots (3)$$

c. Local Homogeneity, Inverse Difference Moment (IDM):

IDM is strongly affected also by the image's homogeneity. Due to the weighting function $(1+(i-j)^2)^{-1}$ IDM will receive small contributions from inhomogeneous areas ($i \neq j$). The result for inhomogeneous images is a small IDM value, and a comparatively higher value for homogeneous images.

$$IDM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i, j) \dots \dots \dots (4)$$

d. Entropy:

In homogeneous scenes, entropy of the first order is low, while a homogeneous scene is highly entropic.

$$ENTROPY = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j) \times \log(P(i, j)) \dots (5)$$

e. Correlation:

Correlation is a measure of linear gray level dependency between the pixels at the specified relative positions.

$$CORRELATION = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i, j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \dots (6)$$

f. Sum of Squares, Variance:

This feature places significantly higher weights on the items which differ from the average $P(i, j)$ value.

$$Variance = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i - \mu)^2 P(i, j) \dots \dots (7)$$

• Gabor Filter:

The Gabor filter extract magnitude at different orientation and scales. For example, a magnitude at 0-degree orientation or at 90-degree orientation (or different scales). This feature can provide accurate time-frequency and it has been found to be remarkably suitable for texture representation and segregation. A sinusoidal plane wave modulated a 2D Gabor filter that is a function of the Gaussian kernel in spatial domain. All filters can be produced by dilation and rotation from one parent wavelet, and hence the Gabor filters are self-similar.

D. Classification

Multiclass SVM aims at assigning labels to places by using vector supporting devices, where the labels are drawn from a finite set of so many elements. The prevailing approach to this is to reduce the single multiclass problem into multiple problems of binary classification. Multiclass SVM consists essentially of the learning module and the classification module where the classification model is applied to new data. It can be implemented by converting single class SVM into multiples of the binary classifications which can be done by distinguishing the classifiers on the basis of the particular label vs the rest(one-versus-all) or between every class pair(one-vs-one). The one-vs-all is based on comparative learning, since the winner takes all the credit as the classifier with the greatest output function assigns the function while the one-vs-one assigns the maximum vote winner principle, in which each classifier assigns the vote to one of the two classes; and finally the class with the most votes determines the winner.

This imaging System consist 6 different classes of melanoma disease which are identified and classified using MSVM. The 6 different types of melanoma are Keratosis, Basel cell carcinoma, Cherry nevus, Dermatofibroma, Melanocytic nevus and Melanoma.

IV. RESULTS

All the experiments were performed in MATLAB. The colour and texture features were extracted using GLCM and Gabor filter and it gives average accuracy of 96.7 % which is far better than referred work performed by using gaussian filter, otsu thresholding and SVM classifier. The results are shown in Table II.

Table II: Average Accuracy of Different Classes

Classes	Accuracy (%)	Specificity (%)	Sensitivity (%)
Actinic keratosis	92%	92%	93%
Basal cell carcinoma	90%	91%	90%
Dermatofibroma	93%	93%	94%
Melanocytic Nevus	93%	92%	95%
Cherry Nevus	91%	92%	91%
Melanoma	93%	93%	94%

A comparison of the average accuracy between our proposed work and referred work is shown in Fig.2. The proposed work has used imfilter, FCM, HSV, GLCM, Gabor Filter and MSVM methods and gives better accuracy than existing work which is 96.7 %.

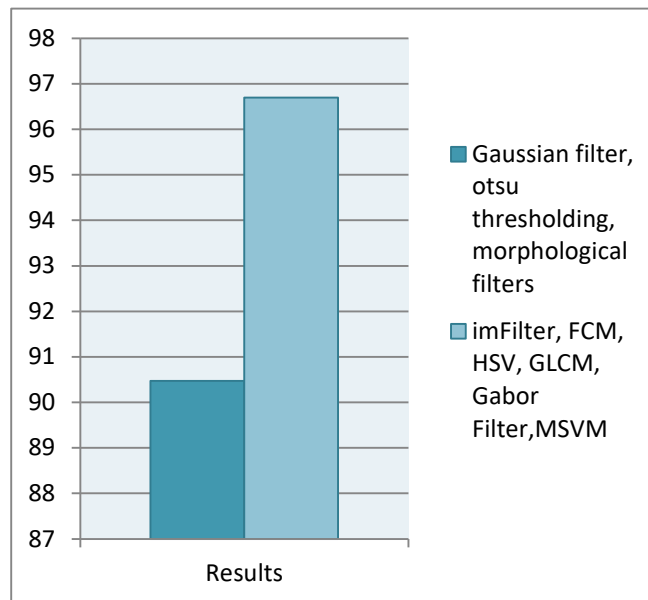


Fig. 2. Average accuracy Graph between Proposed and Referred Work

CONCLUSION

Melanoma is the hazardous skin tumour. The traditional methods taking more time to detect it hence to prevent this life-threatening disease, computer-based system is necessary to be build. Our proposed imaging system classifying the images into six different types of melanoma disease. The results are shown in the table II which provides 96.7% accuracy.

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