

Skin Cancer Detection Using Artificial Neural Networking

Anooja Antony¹, Arun Ramesh², Asha Sojan³, Betsy Mathews⁴, Mrs. Tessy Annie Varghese⁵

UG Scholar, Electronics & Communication Dept., Amal Jyothi College of Engg., Kanjirapally, Kerala, India^{1,2,3,4}

Assistant Professor, Electronics & Communication Dept., Amal Jyothi College of Engg., Kanjirapally, Kerala, India⁵

Abstract: Melanoma is the dangerous form of skin cancer. Rate of melanoma incidence have been increasing nowadays. It is found to be common among non-Hispanic white males and females, but survival rates are high if detected early. Due to the costs for dermatologists to examine every patient, there arises a need for an automated system to assess a patient's risk of melanoma using images of their skin lesions captured using a standard digital camera. One challenge in implementing such a system is locating the skin lesion in the digital image. In the proposed method the image is processed, segmented and features are extracted. Then the features are compared with the given database and classification is done using artificial neural network. The proposed framework has higher accuracy compared to other tested algorithms.

Index Terms: Preprocessing, segmentation, feature extraction, neural networking.

I. INTRODUCTION

Melanoma, also known as malignant melanoma, is a type of cancer that develops from the pigment-containing cells known as melanocytes. Melanoma accounts for approximately 75% of deaths associated with skin cancer.^[1] Melanomas typically occur in the skin but may rarely occur in the mouth, intestines, or eye. In women they most commonly occur on the legs, while in men they are most common on the back. There are different types of skin cancer and some are likely to be fatal. Sometimes they develop from a mole with concerning changes including an increase in size, irregular edges, change in color, itchiness, or skin breakdown.^[2] The primary cause of melanoma is ultraviolet light (UV) exposure in those with low levels of skin pigment. The UV light may be from either the sun or from tanning devices. About 25% develop from moles. Those with many moles, a history of affected family members, and who have poor immune function are at greater risk.^[2] A number of rare genetic defects such as xeroderma - pigmentosum also increase risk. Skin cancers can be classified into melanoma and non-melanoma.

Melanoma is a malignancy of the cells which give the skin its color (melanocytes). The two most frequent types of non-melanoma skin cancer are Basal Cell Carcinomas and Squamous Cell Carcinoma. In addition, there are a number of other less common skin cancers including Merkel cell tumors, cutaneous lymphomas, and sarcomas. The two most frequent types of non-melanoma skin cancer are Basal Cell Carcinomas and Squamous Cell Carcinoma. In addition, there are a number of other less common skin cancers including Merkel cell tumors, cutaneous lymphomas, and sarcomas. Curing rate is 100% if diagnosed at the earliest. Diagnosis is by biopsy of any concerning skin lesion.^[2] Avoiding UV light and the use of sunscreen may prevent melanoma. Treatment is typically removal by surgery. In those with slightly larger cancers, nearby lymph nodes may be tested for spread. Most people are cured if spread has not occurred.

States is 98% among those with localized disease and 17% among those in whom spread has occurred. The likelihood that it will come back or spread depends how thick the melanoma is, how fast the cells are dividing, and whether or not the overlying skin has broken down. Melanoma is the most dangerous type of skin cancer. Globally, in 2012, it occurred in 232,000 people and resulted in 55,000 deaths. Australia and New Zealand have the highest rates of melanoma in the world. There are also high rates in Europe and North America while it is less common in Asia, Africa, and Latin America. Melanoma is more common in men than women. Melanoma has become more common since the 1960s.

II. PROCESS OVERVIEW

The proposed method ensures step-by-step processing. Fig. 1 depicts the system overview. The system overview gives a detailed depiction of the sequence of steps that are to be followed for efficient classification of melanoma.

The step involved are preprocessing, segmentation, feature extraction, classification:

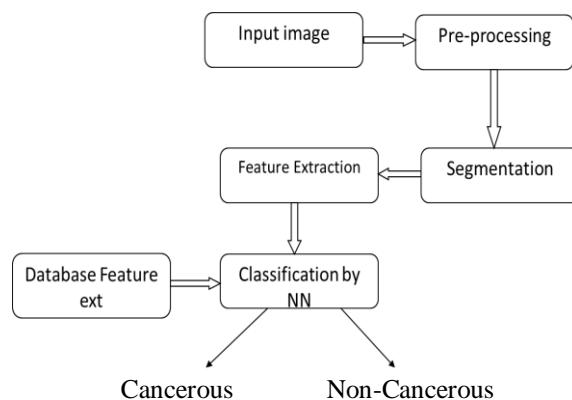


Fig. 1. System overview

A. INPUT IMAGE

Dermoscopy, also known as Dermatoscopy or Epiluminescence Light Microscopy (ELM). ^[3] It is a kind of imaging technique used to examine lesions with a dermatoscope. The process is done by placing an oil immersion between the skin and the optics. Lens of a microscope is placed directly, illuminating sub-surface structures. The lighting can magnify the skin that improve on reveal most of the pigmented structure, different color shades that is not visible to naked eye; and allows direct viewing and analysis of the epidermis. The image obtained from such a dermatoscope is called Dermoscopic Image. These images are then resized into a standard pixel value of 512 x 512.

B. PREPROCESSING

Images are often corrupted by impulse noise due to transmission errors, malfunctioning pixel elements in the camera sensors, faulty memory locations, and timing errors in analog-to-digital conversion. The goal of noise removal is to suppress the noise while preserving image details. ^[4] A variety of techniques have been proposed to remove impulse noise. Noise is perturbations of the pixel values. Noise arises in the sensor or the imaging process. Image filters produce a new image from an original by operating on the pixel values. Filters are used to suppress noise, enhance contrast, find edges, and locate features. To enhance the quality of images, we can use various filtering techniques which are available in image processing. There are various filters which can remove the noise from images and preserve image details and enhance the quality of image. The common noise which contains the image is impulse noise. The impulse noise is salt and pepper noise (image having the random black and white dots). Median filter is the filter that removes most of the noise in image.

C. SEGMENTATION

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images.

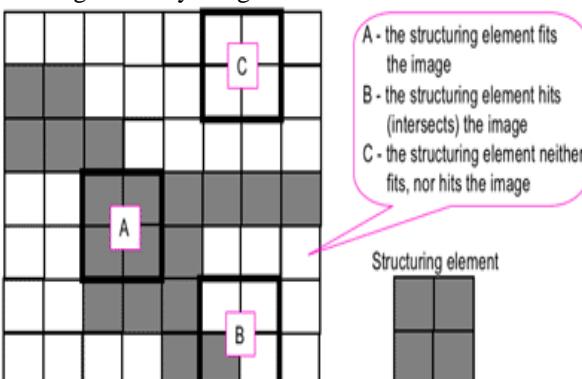


Fig. 2. Probing of an image with a structuring element

^[5] Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is a small binary image, i.e. a small matrix of pixels, each with a value of zero or one. The

pattern of ones and zeros specifies the shape of the structuring element. Some operations test whether the element “fits” within the neighbourhood, while others test whether it “hits” or intersects the neighbourhood as shown in fig 2.

A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image. Zero-valued pixels of the structuring element are ignored, i.e. indicate points where the corresponding image value is irrelevant.

^[6] *Erosion and dilation:* The erosion of a binary image f by a structuring element s (denoted $f \ominus s$) produces a new binary image

$$g = f \ominus s \quad (1)$$

with ones in all locations (x, y) of a structuring element’s origin at which that structuring element s fits the input image f , i.e.

$$\begin{aligned} g(x, y) &= 1, \text{s fits } f \\ &= 0, \text{otherwise} \end{aligned} \quad (2)$$

repeating for all pixel coordinates (x, y) . Erosion removes small-scale details from a binary image but simultaneously reduces the size of regions of interest too. By subtracting the eroded image from the original image, boundaries of each region can be found by,

$$b = f - (f \ominus s) \quad (3)$$

The dilation of an image f by a structuring element s (denoted $f \oplus s$) produces a new binary image

$$g = f \oplus s \quad (4)$$

With ones in all locations (x, y) of a structuring element’s origin at which that structuring element s hits the input image f , i.e.

$$\begin{aligned} g(x, y) &= 1, \text{s hits } f \\ &= 0, \text{otherwise,} \end{aligned} \quad (5)$$

repeating for all pixel coordinates (x, y) .

Dilation has the opposite effect to erosion – it adds a layer of pixels to both the inner and outer boundaries of regions. Results of dilation or erosion are influenced both by the size and shape of a structuring element. Dilation and erosion are dual operations in that they have opposite effects. Let f^c denote the complement of an image f , i.e., the image produced by replacing 1 with 0 and vice versa. If a binary image is considered to be a collection of connected regions of pixels set to 1 on a background of pixels set to 0, then erosion is the fitting of a structuring element to these regions and dilation is the fitting of a structuring element (rotated if necessary) into the background, followed by inversion of the result.

D. FEATURE EXTRACTION

Feature extraction in image processing is a technique of redefining a large set of redundant data into a set of features of reduced dimension. Transforming the input data into the set of features is called feature extraction.

^[7] Feature selection greatly influences the classifier performance; therefore, a correct choice of features is a very crucial step. Various features extracted includes contrast, correlation, energy, entropy, homogeneity:

Contrast: Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.

Correlation: Returns a measure of how correlated a pixel is to its neighbor over the whole image. Its range is between -1 and 1. Correlation is 1 or -1 for a perfectly positively or negatively correlated image.

Energy: Returns the sum of squared elements in the GLCM. It ranges from 0 and 1. Energy is 1 for a constant image.

Entropy: It returns a scalar value representing the entropy of grayscale image. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. **Homogeneity:** Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Its values ranges from 0 to 1. Homogeneity is 1 for a diagonal GLCM.

E. NEURAL NETWORK

[⁸]Artificial neural network (ANN) is a machine learning approach that models human brain and consists of a number of artificial neurons. Neuron in ANNs tend to have fewer connections than biological neurons. Each neuron in ANN receives a number of inputs. An activation function is applied to these inputs which results in activation level of neuron (output value of the neuron). Knowledge about the learning task is given in the form of examples called training examples.

An Artificial Neural Network is specified by:

Neuron model which is the information processing unit of the NN, *an architecture* that contain a set of neurons and links connecting neurons. Each link has a weight, *a learning algorithm* which is used for training the NN by modifying the weights in order to model a particular learning task correctly on the training examples. The aim is to obtain a NN that is trained and generalizes well. The neuron is the basic information processing unit of a NN. It consists of a set of links, describing the neuron inputs with weights W₁, W₂,...W_m, an adder function (linear combiner) for computing the weighted sum of the inputs: Activation function φ for limiting the amplitude of the neuron output. Here bias is denoted as 'b', \

$$\mathbf{u} = \sum_{j=1}^m w_j x_j$$

$$y = \varphi(u + b)$$

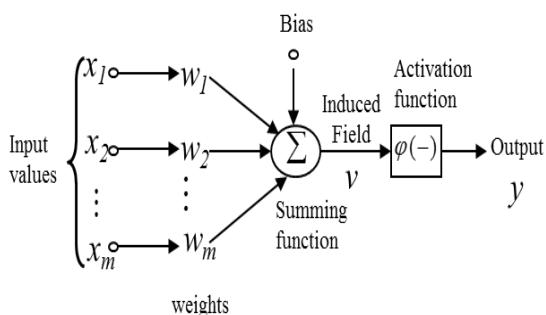


Fig. 3. Neuron Diagram

The neuron diagram is shown in the above diagram where bias b has the effect of applying a transformation to the weighted sum u

$$v = u + b \quad (8)$$

In this proposed system, a feed forward multilayer network is used. The neural network classifier structure consists of Input layer, Hidden layer and Output layer. The hidden and output layer adjusts weights value based on the error output in classification

III. RESULT

This section details the results of automatic classification on images that acquired by means of dermoscopy technique. Database consists of 101 dermoscopy images, previously diagnosed, 45 of them are melanomas and 51 are non-melanomas. GLCM features were used for feature extraction and neural network for classification. 5 features are selected and these input fed to neural input layer. Corresponding values of each features are extracted and then compared with the values of database using neural networking. Fig 5 shows the output of each stages.

The proposed method trained with 75% and tested with 25% of the total number of images. At the end of the training process updated weight values are stored. Then the performance value is measured. Final result is shown in Fig .6

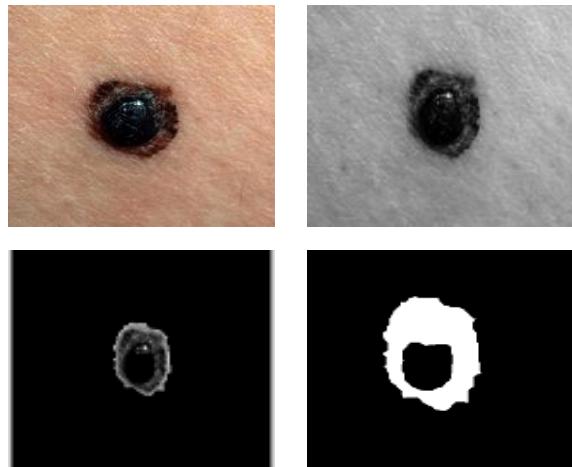


Fig. 5. (a) Input image (b) preprocessed image
(c) Segmented image
(d) modified segmented image

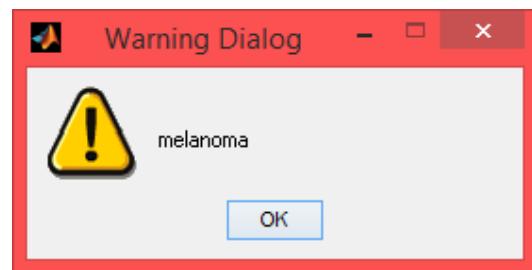


Fig. 6. Final Result

IV. CONCLUSION

A Computer aided skin cancer detection system can achieve a new discovery of detecting benign or malignant skin lesions and separating them from healthy skins. The diagnosing methodology uses Digital Image Processing Techniques and Artificial Neural Networks for the classification of Malignant Melanoma from benign melanoma. Dermoscopic images were collected and they are processed using median filter are used to remove salt and pepper noise. After preprocessing images is segmented using maximum entropy method. Maximum entropy thresholding is used to find out region of interest. The unique features of the segmented images are extracted using feature extraction techniques. This Methodology has got 86.66% accuracy. By varying the Image processing techniques and training algorithms of ANN, the accuracy are improved for this system and the images are classified as cancerous or non-cancerous.

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