Identifing the Levels of Skin Cancer using Texture Distinctiveness

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Abstract:- **Survival rate of skin cancer is high, if detected early it is curable. So an efficient method is necessary to detect skin lesion at the earliest. The cost of dermatoscope screening for the patient is high, there is a need for an automated system to detect skin lesions captured using a standard digital camera. The automated system is to reduce the percentage of error by choosing the appropriate method in each stage. The features used in the system are extracted byusing GLCM (Gray Level Co-Occurrence Matrix). The output of GLCM is given as the input to SVM (Support Vector Machine) classifier which takes training data, testing data and grouping information which classifies whether given input image is cancerous or non-cancerous. The Cancerous image is taken and the Texture Distinctiveness Lesion Segmentation,Texture means shape or subspace. The pixel variation is used to identify the roughness, smoothness, or bumps or other deformations. The Segmentation is achieved by Morphological Operations and the Sobal filter is used for edge detection technique. The feature extraction is based on ABCD (asymmetry, border, colour and diameter).Classify the Skin Cancer images based on their extracted features. And then types and levels of skin cancer can be classified by TDV (Texture Distinctiveness Value).**

***Keywords*:-** *Segmentation, Classification, TDV, GLCM, Sobal Filter.*

I. INTRODUCTION

In human, Skin cancers is the most common form of cancers. The two major types of skin cancer are malignant melanoma and non-melanoma (basal cell, squamous cell, etc.). Melanoma is become more dangerous if not treated. If it detected in its early stages, it is easily curable. Development of automated melanoma screening algorithms have been proposed for reducing the costs of screening melanoma. For locating skin lesion in images automatically, different segmentation algorithms and filters have been proposed. The majority of proposed segmentation algorithms are applicable to digital images, which has better contrast between the lesion and surrounding skin area for certain types of lesions.

II. SYSTEM ANALYSIS

A. Existing System

There is a purposeof a segmentation algorithm designed specifically for digital images of skin lesions. The majority of algorithms only use features derived from pixel color to drive the segmentation. To accurately segment lesions with fuzzy edges is difficult when relying solely on color features. In existing, sparse texture models is used for classification or segmentation of images. It determines a small number of texture representations. Special segmentation algorithms are required to take into account illumination variation, which causes shadows and bright areas to appear throughout the photograph.

B. Proposed System

A GLCM method is proposed for the classification and segmentation of skin lesions. The features are extracted using GLCM. Segmentation is process of removing region of interest from given image. GLCM is used to capture spatial dependency between image pixels. GLCM works on gray level image matrix to capture most common feature such as contrast, mean, energy, homogeneity. In this paper, system output of GLCM is given as input to SVM classifier which takes training data, testing data and grouping information which classifies whether given input image is cancerous or non-cancerous.

The Cancerous image is taken and the Texture Distinctiveness Lesion Segmentation, Texture means shape or subspace. The pixel variation is used to identify the roughness, smoothness, or bumps or other deformations. The Segmentation is achieved by Morphological Operations and the Sobal filter is used for edge detection technique. The feature extraction is based on ABCD(asymmetry, border, colour and diameter).Classify the Skin Cancer images based on their extracted features. And then types and levels of skin cancer can be classified by TDV (Texture Distinctiveness Value).

III. SYSTEM ARCHITECTURE

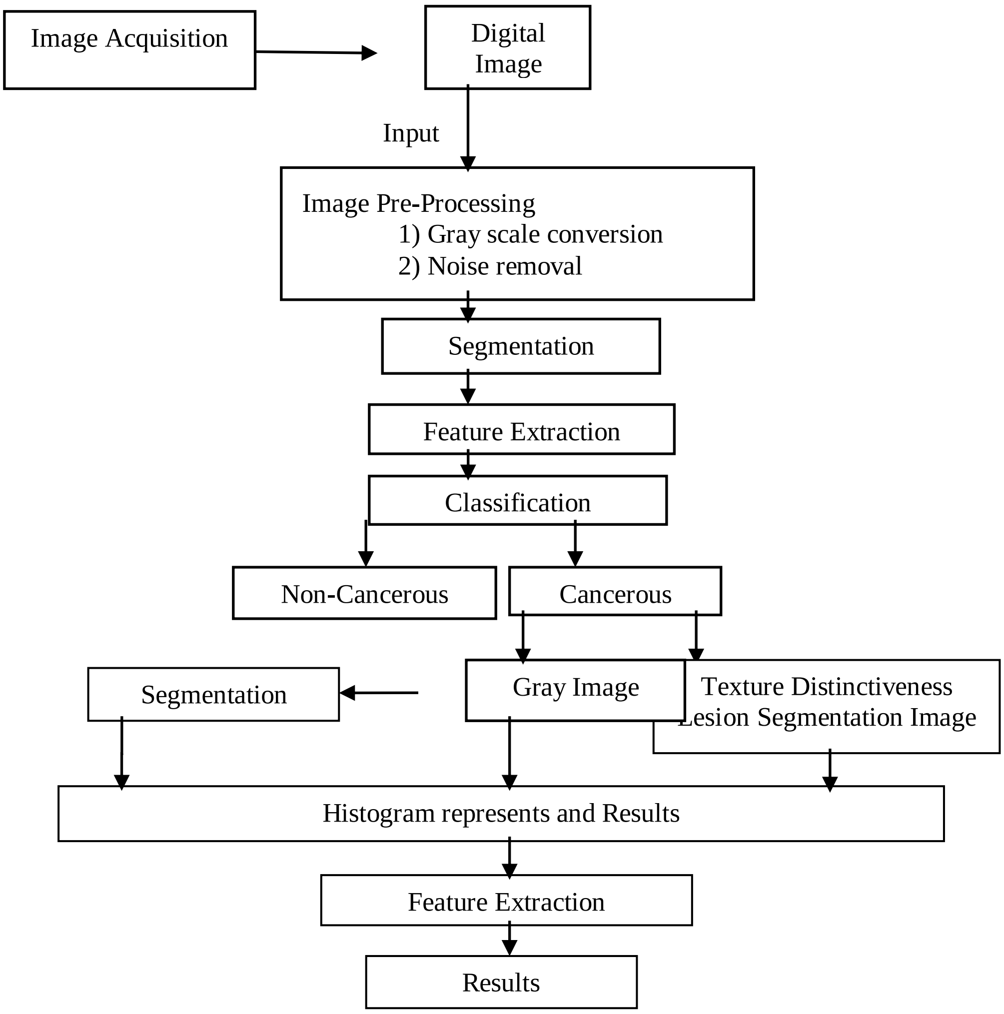

Fig 1:- System Design

A. System Design Discription

The creation of photographic images can be represented as digital image acquisition or digital imaging. After image acquisition, various processing methods can be applied to the image to perform different tasks. The Pre-processing of the image was done by wiener filter. Wiener filter is used for removal of blur in the image. Active contour segmentation segments the image into foreground and background regions.The features are extracted using GLCM (Gray Level Co-Occurrence Matrix). The output of GLCM is given as the input to SVM classifier which takes training data, testing data and grouping information which classifies whether given input image is cancerous or non-cancerous.

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Input images	GLCM VALUES					Output
	CONTRAST	ENERGY	HOMOGENEITY	ENTROPY	MEAN	
	0.0287	0.5532	0.9857	0.7373	0.7036	Yes
	0.0134	0.6672	0.9934	0.5676	0.8017	No
	0.0733	0.5345	0.963	0.8399	0.7282	Yes
	0.0472	0.6476	0.9764	0.6637	0.8118	Yes
	0.0215	0.5242	0.9892	0.7501	0.6530	Yes

Table 1. Example of Training Data

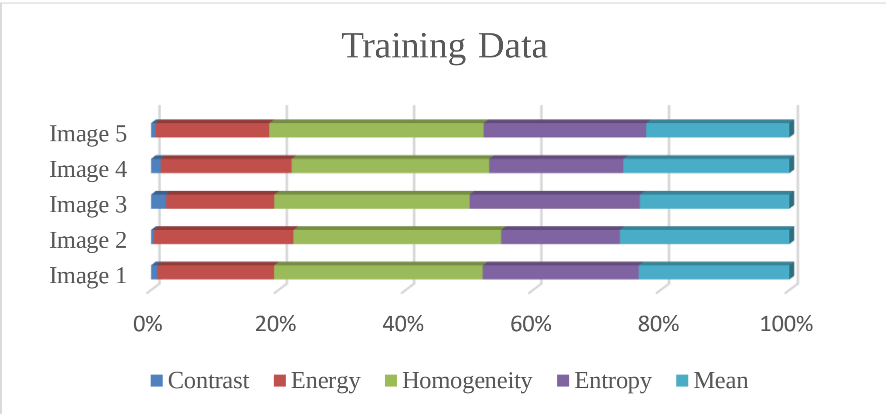

Fig 2:- Training Data Graph

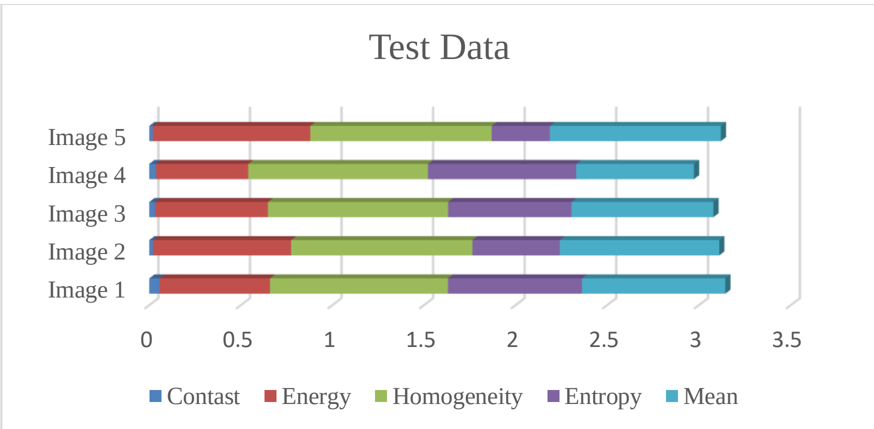

Fig 3:- Testing Data Graph

Input images	GLCM VALUES					Output
	CONTRAST	ENERGY	HOMOGENEITY	ENTROPY	MEAN	
	0.0557	0.6032	0.9721	0.7319	0.7808	Yes
	0.0204	0.7538	0.9898	0.4776	0.8691	Yes
	0.0321	0.6160	0.9839	0.6741	0.7727	Yes
	0.0368	0.5036	0.9816	0.8096	0.6418	Yes
	0.0188	0.8605	0.9906	0.3177	0.9319	No

Table 2. Example of Test Data

B. *Texture Distinctiveness Lesion Segmentation*

Texture means shape or subspace. The pixel variation is used to identify the roughness, smoothness, or bumps or other deformations.

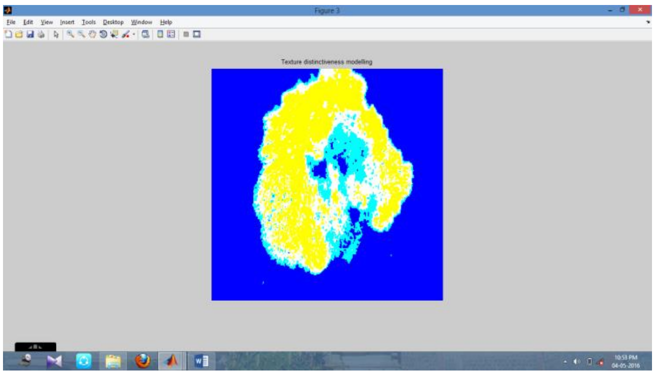

Fig 4:- Texture Distinctiveness Representation

C. *Segmentation*

Segmentation is process of extract the needed (affected) part. We Use Watershed for segment the affected part. Sobelfilter is used for edge detection technique and also use Morphological operations for extract the correct lesion part in the skin image. Morphological operation consists of some functions like Erosion, Dilation.

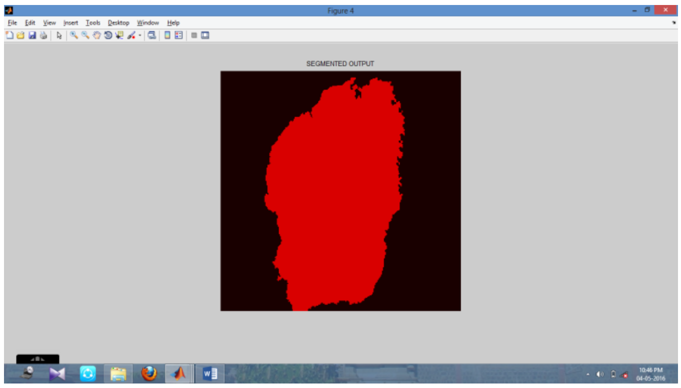

Fig 5:- Segmented Output

D. *Histogram represents and Results*

Histogram represents the color frequency of the image. It helps to extract the color features. The feature extraction is based on ABCD (asymmetry, border, color and diameter).

IV. RESULTS

Classify the types and levels of Skin Cancer images based on their Extracted Features. Thethree major types of skin cancer are:

Basal cell carcinoma (BCC),
Squamous cell carcinoma (SCC),
Melanoma and Nodular Melanoma.

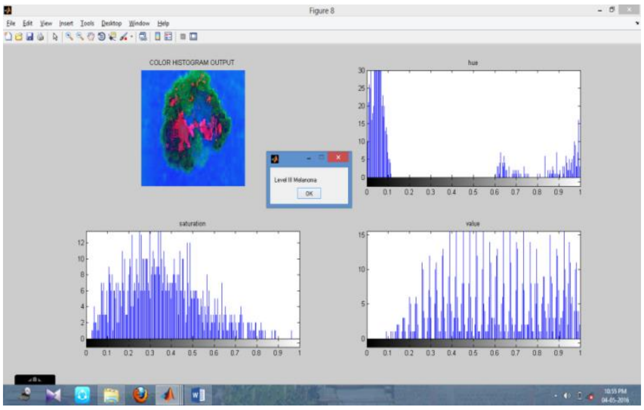

Fig 6:- Output

V. CONCLUSION

In this paper, the features are extracted using GLCM (Gray Level Co-Occurrence Matrix). The output of GLCM is given as the input to SVM (Support Vector Machine).Classifier which takes training data, testing data and grouping information which classifies whether given input image is cancerous or non-cancerous. The Cancerous image is taken and the Texture Distinctiveness Lesion Segmentation, Texture means shape or subspace. The pixel variation is used to identify the roughness, smoothness, or bumps or other deformations. The Segmentation is achieved by Morphological Operations and the Sobal filter is used for edge detection technique. The feature extraction is based on ABCD (asymmetry, border, colour and diameter).Classify the Skin Cancer images based on their extracted features. Then types and levels of skin cancer can be classified by TDV (Texture Distinctiveness Value).

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