CLASSIFICATION OF MELONOMA AND NEVUS FOR DIAGNOSIS OF SKIN CANCER

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Abstract — *Melanoma is viewed as a lethal kind of skin malignant growth. Be that as it may, it is here and there difficult to recognize it from nevus because of their indistinguishable visual appearance and manifestations. The death rate due to this ailment is higher than all other skin-related solidified malignancies. The quantity of cases is developing among youngsters, yet in the event that it is analyzed at a previous stage, at that point the endurance rates become extremely high. The expense and time required for the specialists to analyze all patients for melanoma are high. In this paper, we propose a smart framework to recognize and recognize melanoma from nevus by utilizing the cutting edge picture handling strategies. From the start, the Gaussian channel is utilized for expelling clamor from the skin sore of the obtained pictures followed by the utilization of improved K-mean bunching to portion out the injury. A particular cross breed superfeature vector is shaped by the extraction of textural and shading highlights from the injury. Bolster vector machine (SVM) is used for the order of skin disease into melanoma and nevus. Our point is to test the viability of the proposed division strategy, separate the most reasonable highlights, and contrast the arrangement results and different procedures present in the writing. Our proposed technique chronicles empowering results having 96% accuracy.*

Key Words: Melanoma, nevus, feature, K-means clustering, and centroid selection

1. INTRODUCTION

Skin disease is the uncontrolled development of skin cells, harming cell DNA and activating changes that prompt cells to increase quickly and structure threatening tumors. The three unique kinds of skin malignancy are basal cell carcinoma, squamous cell carcinoma and melanoma. Basal cell carcinomas happen in the basal cell layer of the skin, which is the lower layer of the epidermis. These malignancies will in general develop gradually and typically create in regions which are presented to the sun, for example, the head and neck. Squamous cell carcinomas happen in the external layers of the skin. They dive deep into the skin and as a rule happen on the face, ears, lips, and hands, and eject into constant skin wounds. Melanoma creates from the melanocyte cells of the skin, which produce a shade considered melanin that makes skin earthy colored or dark. It ordinarily creates in the most profound layer of the epidermis and develops profound into the skin, and is called intrusive melanoma. It attacks the lymph hubs and veins and can spread to removed pieces of the body.

According to the research, the mortality rate may be reduced up to 90 %, if the skin cancer is diagnosed at an initial stage, Hence the diagnosis and classification of the skin cancer in its early stage are vitally important [4], [5]. Among the conventional approaches followed by researchers to detect melanoma and nevus is ABCD rule [5]. A total dermoscopic score is obtained for each of the ABCD features where *A* represents Asymmetry, *B* is for Border irregularity, *C* represents color variations and *D* is for the Diameter. Each respective feature is assigned an individual weight based on their significance in the feature space. Based on the calculated score the lesion is identified as cancerous or benign.A7-point Checklist is another technique that is used to identify skin cancer in dermoscopic images. The list target symptoms of atypical pigment network, grey-blue areas and atypical vascular pattern, streaks, blotches, irregular dots and globules, and regression patterns. At times when these symptoms are identified, a medical professional is consulted for the treatment [8]. Later on, the checklist reduced to a lesser number of features of the different network, Asymmetry and blue-white structures[9]. Considering the complex nature of melanoma, it becomes hard for the researchers to detect skin cancer only on the basis of these geometrical features. Another problem is that the size of the image database is increasing dramatically. So the practicality of such information is dependent on how well it can be accessed, searched and how well the relevant knowledge can be extracted from it.

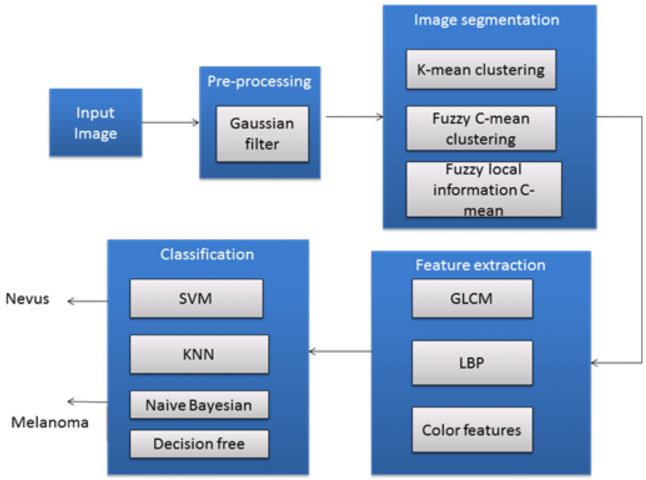

Fig-1 BLOCK DIAGRAM OF PROPOSED METHOD

2. METHODOLOGIES

Skin cancer is measured as a major contributor to the causes of deaths around the world. There are various types of cancers that are discovered and battled with. However, skin cancer is amongst fast-growing cancer nowadays. According to modern research, patients with a skin cancer diagnosis is significantly increasing more than any other cancer form every year. Melanoma is the most common form of skin disease that affects the skin surface cells known as melanocytes. It consists of cells that cause the skin to turn to black color. Melanoma can be found in dark or darker color yet at some point it might likewise be in the skin, pink, red, purple, blue or white color. This form of cancer is very disturbing due to its tendency to cause metastasis, i.e. ability to spread. Detecting skin cancer at the initial stage can help in reducing the risk factor in patients.

In this paper develop a complete automated computer - aided system to detect melanoma cancer accurately. The input images contains noise. To remove the noise in the input images Gaussian filter is used as pre-processing. The three segmentation algorithms are used in proposed system. Design of an improved K-Mean clustering, Fuzzy C- Mean , Fuzzy Local Information C- Mean techniques for computationally efficient segmentation. Utilization of hybrid features incorporating both texture and color of the lesion. For classification purpose we use four classifiers are SVM, KNN, Naive bayesian, Decision Trees. The purpose of classifier is used to find the type of skin cancer present in the given image. The performance of the classifiers are measured by the following parameters such as sensitivity, specificity, accuracy, precision.

2.1 Pre-processing

Medical images are often susceptible to noise mainly due to bad illumination, hair and air bubbles. This inclusion of noise in images results in the formation of artifacts. Due to such artifacts, the segmentation results may get affected causing inaccurate detection results. Therefore, Noise removal is a significant step before applying any segmentation or feature extraction technique for an accurate diagnosis. To smoothen the image, Gaussian filter is highly recommended as it removes the speckle noise added during the process of acquisition. Gaussian kernel coefficients are sampled from the 2D Gaussian function.

2.1.1 Gaussian filtering

When working with images we need to use the two dimensional Gaussian function. This is simply the product of two 1D Gaussian functions (one for each direction) and is given by:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Gaussian filter properties:

- ✓ Most common natural model.
- ✓ Smooth function, it has infinite number of derivatives.
- ✓ Fourier transform of gaussian is Gaussian.
- ✓ Convolution of a Gaussian with itself is a Gaussian.
- ✓ There are cells in eye that perform Gaussian filtering

2.2 Image Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as image objects). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. In the proposed method we use 3 types of segmentation algorithm. They are

- ✓ K-means clustering algorithm
- ✓ Fuzzy C-means clustering
- ✓ Fuzzy local information C-mean

2.2.1 K-means clustering algorithm

The K-means clustering algorithm clusters data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel in the closest mean.

2.2.2. Fuzzy C-means clustering

FCM is an unsupervised clustering algorithm that has been successfully applied to a number of problems. FCM adopts fuzzy partitions to make each given value of data input between 0 and 1 in order to determine the degree of its belonging to a group. FCM is a fuzzy clustering method allowing a piece of data to belong to two or more clusters.

2.2.3 Fuzzy local information C-mean

An enhanced FCM method is acquainted with segment the image which is influenced by noise, outlier or some other artifact. The tradeoff weighted fuzzy factor depends at the same time on the space separation of every neighboring pixel and their gray level contrast.

2.3 Feature extraction

Once the lesion is segmented out of the background skin, it is then classified as malignant or benign. For better classification results, it is required to use the best feature descriptors for machine learning modeling. The Increase in the number of features increases the computational cost, inspiring the description of precise decision boundaries. Thus, it is ensured that a distinctive feature set is used. A lesion is characterized by its texture and its color. In this research work three different features using Local Binary Pattern (LBP), Grey Level Co-occurrence Matrix (GLCM) and RGB color channel features, are extracted from the ROI of skin lesion. The techniques are utilized to extract the textural and color-based features from the input skin lesion.

2.4 Classification

After segmentation and feature extraction, the hybrid feature vector is then provided to classifiers to identify the melanoma and nevus. Different classification algorithms are trained and tested in the proposed. They are,

- ✓ SUPPORT VECTOR MACHINES
- ✓ K-NEAREST NEIGHBOR
- ✓ NAIVE BAYESIAN
- ✓ DECISION TREES

Support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.

K-nearest neighbors (KNN) is a machine learning algorithm that keeps all training values and classifies new ones based on a similarity measure as given in the equation below.

$$d = \sqrt{\sum_{i=1}^{K}(x - y_i)^2}$$

Naive Bayes classifier. In machine learning, naïve Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naïve) independence assumptions between the features. They are among the simplest Bayesian network models.

A decision tree is the flowchart representation of attributes in the form of a tree where each attribute acts as a node. The tree is formed with the best attribute as the root node and then passes through each attribute following the way down to the leaf node i.e. its respective class.

RESULT AND DISCUSSION

The skin images are acquired from DermIS dataset. The first is a subset of a DermIS database (Dermatology Information System, available online: http://www.dermis.net) that contains macroscopic photographs with lesion diagnosed as melanoma and diagnosed as non melanoma.

A true positive represents when melanoma is classi_ed by the system as a melanoma while true negative happens when a lesion belongs to nevus and classi_ed as a nevus. On the other way, a predicted false positive value happens when a lesion is not melanoma and it is classi_ed as melanoma while a false negative happens when a certain lesion is melanoma and is classi_ed as nevus.

Fig-1 Input image

Fig-2 Pre-processing image

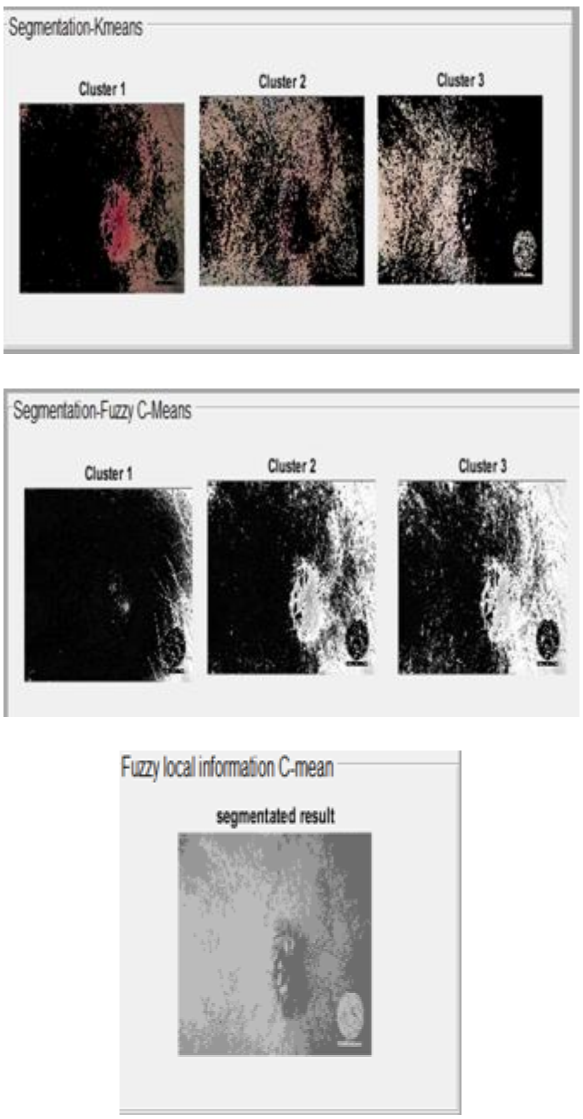

Fig-3 Segmented images

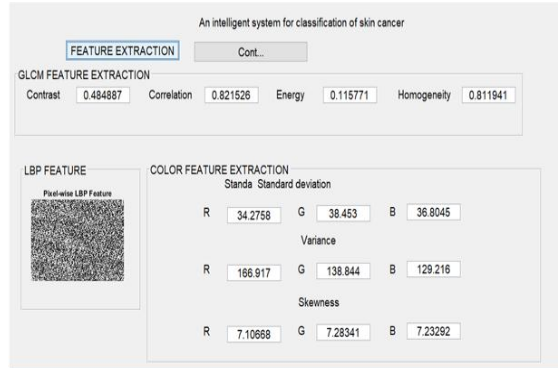

Fig-4 Feature extraction

Fig-5 Classification

CONCLUSION

In this project, introduced a keen framework for grouping of skin malignant growth into melanoma and nevus. It is seen that serious issue that causes the misclassification is injury identification and division. The K-mean bunching strategy utilizing centroid choice is utilized to remove the ROI from the malignant growth picture all the more precisely and productively. Textural and shading highlights extraction methods are utilized to get most appropriate highlights for characterization. For surface highlights, GLCM and LBP highlights are joined with the shading highlights to accomplish a high characterization precision of 96%. Along these lines, our proposed procedure has had the option to arrange skin malignant growth pictures into melanoma and nevus all the more precisely and productively.

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