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MELANOMA DETECTION USING FEED FORWARD NEURAL NETWORK AND THERAPEUTIC SUGGESTION

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Abstract - *Melanoma is potentially lethal cancer which is most commonly cutaneous. The worldwide incidence of melanoma has risen rapidly over the past few years. Due to the identical visual appearance and symptoms, it is complex to distinguish melanoma from nevus. It has a higher mortality rate when compared to all other skin-related malignancies but the survival rate can be improved if it is diagnosed at an initial stage. since it is tedious and expensive for the oncologist to individualize melanoma from nevus they advised for automated systems. Here we propose an intelligent system to distinguish melanoma from nevus by using the art of digital image processing techniques. At first, the noise in the acquired images is removed with the help of the median filter then the improved K-mean clustering method is used for the segmentation of the clusters and a Feedforward neural network classifier is utilized for the classification of melanoma and nevus. Finally, the result is tested on a medical dataset*.

***Key Words*: Melanoma, Nevus, K-means clustering, Feature Extraction, and feed-forward neural network**

1.INTRODUCTION

According to a recent survey, melanoma is identified as a major contributor to the causes of death around the world. various types of cancers are discovered and battled with. However, skin cancer is considered as the rapidly increasing cancer nowadays. Melanoma is a familiar form of skin cancer that affects surface cells (melanocytes) of the skin. Due to those toxic cells, the skin is turning to black color. Melanoma can be found anyplace on the body but it is mostly found in dark or darker color regions yet at some point, it might likewise be present in the light shades. It is mostly found in the posterior region of the legs. This type of cancer is ominous due to its tendency to metastasis. Our research work aims to achieve immense accuracy of results in determining and classifying melanoma from the nevus. The list of 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. Later on, the checklist reduced to a lesser number of features of the different network, Asymmetry, and blue-white structures. Considering the complex nature of melanoma, it becomes hard for the researchers to detect skin cancer only based on the 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. With the advent of computer-aided diagnostic systems, researcher mainly emphasizes on the automatic detection and classification of skin cancer. Medical images in the form of textural features, geometric features, color features and in a combination have been used to identify and classify skin cancer diseases. However, it is still a challenging task to identify the most discriminative features for identifying melanoma at its initial stage. The design of an improved K-Mean approach for computationally efficient segmentation of the affected cells and utilization of hybrid features incorporating both texture and color of the lesion. The remaining of our research paper is organized as a detail literature review of existing techniques of features extracting and classification is discussed in upcoming sections.

1.EXISTING SYSTEM

Extensive research has been done in the respective domain by the discovery and development of new approaches to accurately diagnose skin cancer. Related work can be divided into three types based on features extraction technique i.e. geometrical, textural, and color. These techniques are individually discussed in detail below.

1.1.GEOMETRICAL FEATURES

The ABCD-E system [1], [2], [3], 7-point checklist [4], [5], 3-point checklist [6] offers geometrical features techniques that are used for classification of the melanoma. According to Johr [7], the features extracted by the ABCD rule is computationally less expensive for the 7-point checklist. It is also observed that the consistency in the clinical diagnosis is at a higher rate for the ABCD rule. So, most of the computer-aided systems for melanoma detection used ABCD rule for feature extraction. Though, the ABCD technique is more prone to over classification of nevi as melanoma [8].In the research work of Kasmiand Mokrani [9], extracted the characteristics of ABCD attributes and combines with color asymmetry and dermoscopic structures. The proposed system achieved 91.25% sensitivity. In another study [10] the author tried to investigate the possibility to automatically detect the dermoscopic patterns based on ABCD rule using deep convolutional neural networks. Experimental results demonstrated 88% accurate classification of skin cancer. In another research study, Moussaetal.[11] used ABCD rule excluding the color from the traditional ABCD, because color requires an additional large amount of computer resources. They utilized KNN as a classifier achieving 89% accuracy. It is also observed that the ABCD rubric is sometimes a very qualitative and subject manner that results in large inter-observer and intra-observer bias [12]. For this purpose, High-quality intuitive features (HLIF) approach is used that represents the asymmetry characteristic of ABCD rubric from skin cancer images [13]. The system achieved 86% accuracy from the extract's set of features. Later Amelard et al. [14] extended his previous work by proposing six new HLIF features for different color channels. Experimental results show a better classification accuracy.

1.2.COLOR FEATURES

The color features can be extracted based on the statistical value calculated from color channels. They are Mean color, variance color and standard deviation value of the RGB or HIS color model. Some of the different color features extraction techniques consist of color asymmetry, centroid distance and LUV histogram distance [15], [16]. In another study [17], the author classified the melanoma based on global and local descriptors. They combined the textural features with the color obtained classification scores of SE and SP are 93%, 95% respectively. Other researchers used the same approach using color features with a set of textural and shape-based features. Ganster et al. [18] used color and shape-based features from skin lesions with KNN classifier. The number of images taken for the experimentation purpose is more than 5300 and they achieved 87% and 92% sensitivity and specificity respectively. Rubegni et al. [19] also utilized textural and geometrical features and achieved a sensitivity of 96% and specificity of 96%. Celebi et al. [20] used a large features vector consisted of color, shape and texture features. The SVM achieved a sensitivity of 93% and specificity of 92%. Almansour et. al in [21] used color moments with textural features with SVM as classifier achieved 90 % accuracy with 227 melanoma and nonmelanoma skin cancer images.

1.3.TEXTURAL FEATURES

Image texture represents the spatial distribution of pixel intensity levels in an image. Textural features represent the underlying pattern and layout of intensity levels acting as one of the most distinctive features for object or region of interest identification. When it comes to skin cancer, textural features are frequently used for image analysis as it helps in classifying between nevus and melanoma by calculating the irregularity of their structure [22]. It is observed that interest is increasing in the computerized examination of digital images taken by the Dermoscopic process.

2. PROPOSED METHODOLOGY

We have conferred the components of our scheduled methodology in this part. Input images seized from the datasets endure the quality enhancement through pre-processing techniques. Later the ROI from the skin lesion is extracted which are further processed for significant feature extraction and finally classifying them into melanoma or nevus. In the figure below the proposed methodology where each stage is briefly discussed in the section below.

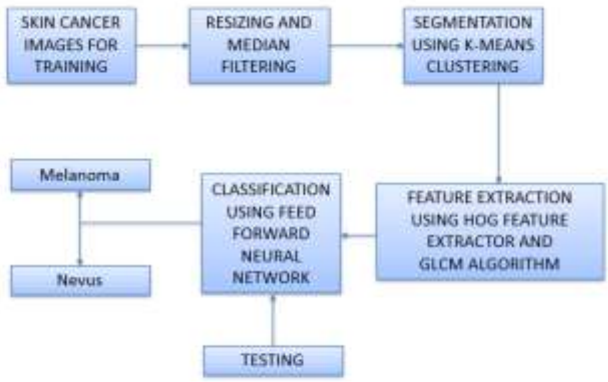

Fig-1, The process of classification

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, the median filter is highly recommended as it removes the speckle noise added during the process of acquisition.

2.2. MEDIAN FILTER

The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise. Algorithm description**,** The main concept of the median filter is to run through the signal entry by entry and substituting each entry with the median of neighboring entries. The pattern of neighbors is known as a window, which slides over the entire signal. For 1D signals, the first few preceding are considered in 1D signaling and following entries for 2D or higher-dimensional signals such as images, more complex window patterns are possible in 2D such as box or cross patterns. If the window has an odd number of entries, then the median is simple to define and in this, just the middle value after all the entries in the window are sorted numerically. whenever there is an even number of entries, there is a possibility of more than one solution. To explain it, a window size of three is observed in which one entry immediately preceding the first and for the following each entry of a median filter will be applied, the following simple 1D signal

x = [2 80 6 3]

So, the median filtered output signal y will be:

y[1] = Median[2 2 80] = 2

y[2] = Median[2 80 6] = Median[2 6 80] = 6

y[3] = Median[80 6 3] = Median[3 6 80] = 6

y[4] = Median[6 3 3] = Median[3 3 6] = 3

i.e. y = [2 6 6 3].

Note that, in the example above, because there is no entry preceding the first value, the first value is repeated, as with the last value, to obtain enough entries to fill the window. This is one way of handling missing window entries at the boundaries of the signal, but other schemes that have different properties. Code for a simple 2D median filter algorithm might look like this: allocate output Pixel Value [image width][image height]

allocate window[window width * window height]

edgex := (window width / 2) rounded down

edgey := (window height / 2) rounded down

for x from edgex to image width - edgex

for y from edgey to image height - edgey

i = 0

for fx from 0 to window width

for fy from 0 to window height

window[i] = inputPixelValue[x + fx - edgex][y + fy - edgey]

i = i + 1

sort entries in a window[ ]

output Pixel Value[x][y] = window[window width * window height / 2]

this algorithm processes one color channel only and it takes the not processing boundaries approach.

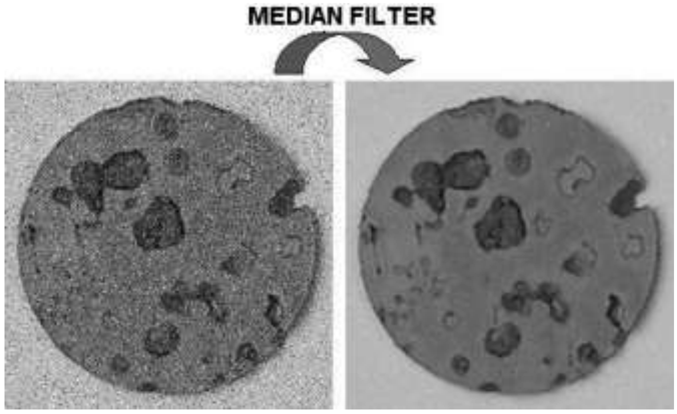

Figure.2

2.3. K-MEANS CLUSTERING

K-mean clustering is one of the common machine learning technique which is extensively used in many applications such as data mining, image processing, pattern recognition, etc. K-mean works on the basic methodologies of grouping and clustering of extracted data into K number of clusters. In which based on their intensity levels the image is split into non-overlapping groups .where selecting the centroids on the obtained data-points is the initial step, which is selected randomly or by using certain criteria. The pixels or data-points are clustered based on their minimum distance from the selected centroids. After each iteration, the mean values of the formed clusters are found and are set as the centroids for the next iteration. The iterative process repeats itself until there is no variation in the successive cluster centroids. The proposed K-Mean initializes its centroids by centroid selection technique as given in equation 2 below.

$$Mu = (1:K) * m / k + 1$$

where K is the number of clusters, m is the maximum value of a pixel in the image, and k goes from 1 to K. The centroid selection technique works by ensuring significant difference among the values of initialized centroids making it more efficient and robust by converging to the final position in a lesser number of iterations. In our proposed system, the input images with affected lesion are observed along with the background skin.we have taken the value of k as 2, such that the affected lesion are extracted from the unaffected background skin.

3.FEATURE EXTRACTION AND CLASSIFICATION

The features are extracted using a Histogram Of Orientation(HOG) and Grey Level Co-occurrence Matrix Functions(GLCM). In HOG the image is divided into a cell of size NxN pixels. The orientation of all pixels is computed and accumulated in an M-bits histogram of orientation. Grey level co-occurrence matrix is a global textural feature extraction technique computing the statistical distribution of intensities in combination at specific positions in the image. Based on the number of contributing intensity levels in the combination, the order of the statistics is determined. GLCM extracts the second-order statistical texture features by considering the spatial relationship of two intensity levels A two-layered feed-forward neural network was employed to classify the images. Here the conjugate gradient algorithm is used as the training algorithm. It accurately locates the minimum in a finite number of iterations. It is well suited for the problems which are having a large number of parameters. Here the software used is MATLAB. MATLAB is an efficient tool to develop applications based on neural networks. MATLAB environment integrates graphic illustrations with precise numerical calculations and is a powerful tool for performing all kinds of computations. In addition to standard functions there exist a large set of toolboxes. In this work, we trained four different networks for the detection of exudates, hemorrhages, vessels and new blood vessels. The network consisting of an input layer, a hidden layer, and output layer is shown in Fig. 3

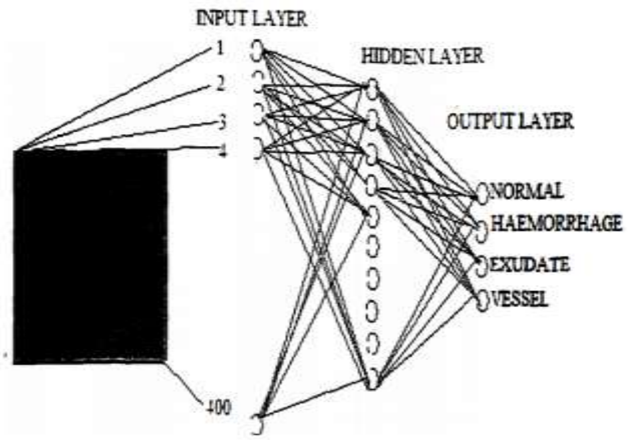

Fig.3, Input layer, Hidden layer and Output layer

4. RESULTS AND DISCUSSION

The segmented region in the skin cancer images describes cancer affected lesion. This cancerous lesion needs to be extracted from the background skin information .K-Means clustering using centroid selection has been utilized for the segmentation of the input images based on the variation in the intensities with the value of K is set as 2. The clusters which are formed over the images are then utilized for further processing of the image using this melanoma is detected accurately. Figure 4,5,6, and 7 shows the resized, noisy, filtered and segmented results. The ground truth data of the image is marked on it inside our dataset with the help of the physician and the affected region and boundaries are identified with the help of it. The K-Mean segmentation technique extracts the region of interest from the images and segments out the cancer-affected regions from the background. To measure the segmentation accuracy of a system the percentage of overlap between the segmented area and the ground truth information is calculated. It is achieved through the Jaccard Index. For an image with segmented region A, Jaccard Index of similarity with the ground truth image B is calculated as,

$J(A,B)= |A \cap B|\ |A \cup B|$

Using improved K-Mean 94% of the images were accurately segmented and the data is maintained on the IoT platform for future references.

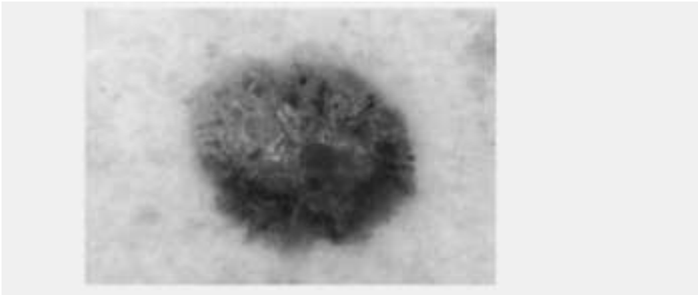

Fig.4, Resized image

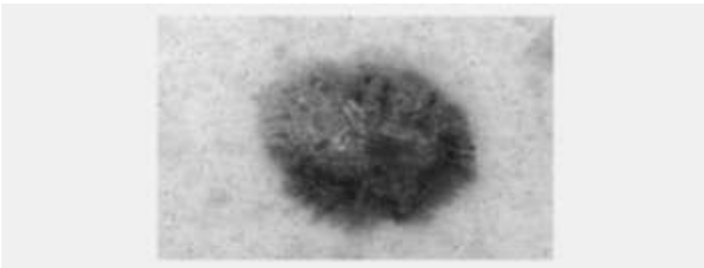

Fig.5, noisy image

Fig.6, Filtered image

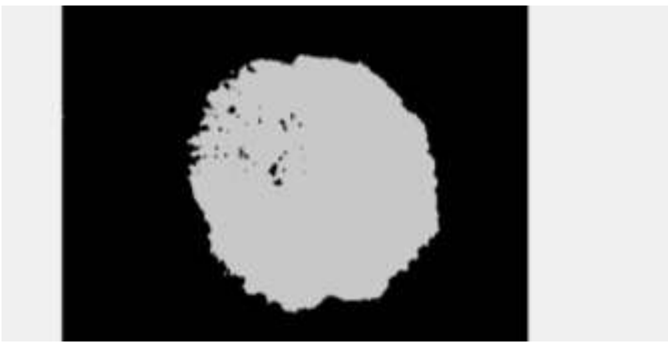

Fig.7, segmented image

5. CONCLUSION

In this research paper, we presented an intelligent system for the classification of skin cancer into melanoma and nevus. It is observed that major problem that causes the misclassification is lesion detection and segmentation. The K-mean clustering technique using centroid selection is used to extract the ROI from the cancer image more accurately and efficiently. Textural and color features extraction techniques are used to obtain best-suited features for classification. For texture features, GLCM and LBP features are combined with the color features to achieve a high classification accuracy of 96%. In this way, our proposed technique has been able to classify skin cancer images into melanoma and nevus more accurately and efficiently. The effectiveness and performance of the proposed approach are validated on DermIS image dataset and the medicine suggestion is also provided using the Internet of Things.

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