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CLASSIFICATION OF MELANOMA AND NEVUS IN SKIN CANCER LESIONS

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ABSTRACT - Melanoma that produces melanin pigment that gives your skin its colour. Melanoma can be successfully treated if it is detected early. Melanomas can develop anywhere in your body. They most often develop in areas that have had exposure to the sun. Melanomas can also occur in areas that don't receive much sun exposure, such as the soles of your feet, palms of your hands and fingernail beds. These hidden melanomas are more common in people with darker skin. Thus, we presented an intelligent system for 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 colour features extraction techniques are best suited features for classification. For textural features, GLCM and LBP features are combined with colour features to achieve a high classification accuracy of 90%. 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

Keywords: Melanoma, Nevus, Detection, Segmentation, Extraction, GLCM and LBP.

I. INTRODUCTION

Skin cancer is among the most commonly worked out cancers; of which damaging melanoma is by far its most war-like form. Happily, when melanoma is worked out in an early stage, it can easily be given attention to through a simple taking out with a cut of the wound. As an outcome of that, several diagnosis techniques have been had a look for to get well the early discovery of melanoma. Melanoma and Non-Melanoma are chief groups of skin cancers. Damaging melanoma is of several sub-types. Basal unit carcinoma and squamous unit carcinomas are 2 main types of non-melanoma skin cancers. Each sort of skin cancer is different from the other skin cancers in certain qualities. Generally skin cancer is screened by clinicians through seeing observation. The rule for cancer detection is called as ABCD rule which is given by A : asymmetry (one half of the mole does not match the other half) B : border irregularity (edges of the mole are ragged, notched, or blurred) C : color (pigmentation of the mole is not uniform, with varying degrees of tan, brown, or black) D : diameter of more than inch (about the size of a pencil eraser) E : evolving (the mole is changing over time) Seeing going-over of clinicians for skin cancer does not be responsible for 100% discovery and sometimes it may lead to possible & unused quality damage. possible & unused quality cause damage includes unnecessary procedures such as skin biopsy or taking out with a cut for wound that do not turn out to be cancer or sometimes the wound might have missed and not have gone for biopsy, coming out in death. As an outcome there is a clear thing needed for automatic discovery 5 system for skin cancer which should be highly good at producing an effect and accurate. The offered careful way form of 2 Major steps

1. Preprocessing which takes away the things like hair, ink marking and lighting-on bad, wrong points.
2. Breaking down into parts of wound using k-means clustering.

II. LITERATURE SURVEY

One of the first instruments used to determine if a skin lesion is malignant or benign is medical detection algorithms. Nachbar et al. [1] devised a subjective technique based on the lesion's visual appearance. The ABCD Rule is based on the colour, shape, and specific characteristics of skin lesions. It is one of the most commonly used algorithms for evaluating a lesion using a naked eye exam or a dermatoscope due to its simplicity.

Adjed et al. [2] proposed a method in which statistical metrics and texture features such as local binary pattern are generated after fusing structural information with Curvelet and Wavelet transforms utilising the Fast Digital Curvelet Transform (FDCT) wrapping approach. Using the PH2 dataset [19], they concatenated roughly 200 features.

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Hagerty et al. [3] created a fusion approach that uses a transfer learning method based on the ResNET-50 Convolutional Neural Network (CNN) architecture to extract deep features from images. The subject of which craftsmanship features are utilised in their process, on the other hand, is unclear. Furthermore, they used two datasets: the private set and the second set (a modified version of the ISIC 2018 dataset) for performance revision, applying a feature selection approach, in this case, the χ^2 method [4].

Li et al. [5] employed a deep learning strategy with the fusion of clinical criterion representations, using a boosting tree-learning algorithm dubbed Light GBM as a classifier and fusion method. Color properties (RGB and HSL features), texture properties (SIFT and LBP), and shape properties are all used with this method (solidity and circularity, image ratio, and area ratio). The transfer learning method was used to obtain the deep learning features, which were based on the ResNET-50 and DenseNET-201 CNN architectures. The ISIC 2018 dataset [4] was used to process data for 566 characteristics.

Thiyaneswaran B et al.(2020) proposed k-mean clutsering methods used for the detection and segmentation of cancer area in skin images. The authors have obtained 90% of accuracy in the cancer area detection[15]. Kumarganesh et.al. (2018) suggested an ANFIS classifier technique for the classification of tumors from the origin images. The authors obtained the 96.6% of classification accuracy [16]. Kumarganesh et.al. (2016) proposed an ANFIS classifier method for the classification of tumors from the original images. They achieved 93.07% of sensitivity, 98.79% of specificity, and 97.63% of cancer segmentation accuracy [17].

Abbas and Celebi [18] suggested a CAD system in which a Stack-Based Auto-Encoder (SAE) extracts deep features from pixels of a lesion while minimising information loss[19]. Color (the Hill climbing algorithm (HCA)) and texture (the speed-up robust features (SURF)) are retrieved from the handmade features. They used Principal Component Analysis (PCA) in a feature fusion technique, then Recurrent Neural Networks (RNN) and a Softmax Linear Classifier in the final stage.

III. PROPOSED METHODOLOGY

Our proposed system tackles the fundamental problem of detecting the skin cancer. Moreover, it tackles the major problem of detecting and classifying the type of skin cancer.

Module 1: *IMAGE PROCESSING USING* GAUSSIAN FILTER

Image filters can be used to reduce the amount of noise in an image and to enhance the edges in an image. Enhancing the edges of an image can help a model detect the features of an image. The Gaussian Filter is similar to the mean filter however it involves a weighted average of the surrounding pixels and has a parameter sigma. The kernel represents a discrete approximation of a Gaussian distribution. While the Gaussian filter blurs the edges of an image (like the mean filter) it does a better job of preserving edges than a similarly sized mean filter. The 'Gaussian Blur' function from the Open-CV package can be used to implement a Gaussian filter. The function allows you to specify the shape of the kernel. You can also specify the standard deviation for the x and y directions separately. If only one sigma value is specified then it is considered 21 the sigma value for both the x and y directions.

Module 2: *IMAGE SEGMENTATION USING K-MEANS CLUSTERING*

K-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. This algorithm aims at minimizing an objective function know as squared error function given by:

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{ci} \left(\|x_i - v_j\| \right)^2$$

where,

'$\|x_i - v_j\|$' is the Euclidean distance between x_i and v_j. 'ci' is the number of data points in ith cluster. 'c' is the number of cluster centers.

1) Randomly select 'c' cluster centers.
2) Calculate the distance between each data point and cluster centers.
3) Assign the data point to the cluster center whose distance from the cluster center is minimum of all the cluster centers.
4) Recalculate the new cluster center using: $vi = 1\ ci \sum xi\ ci\ j$=1 where, 'ci' represents the number of data points in ith cluster.
5) Recalculate the distance between each data point and new obtained cluster centers.
6) If no data point was reassigned then stop, otherwise repeat from step 1.

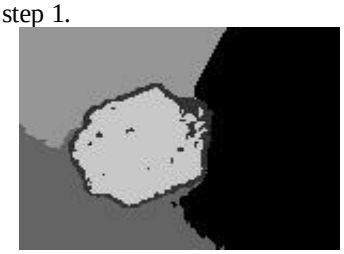

Fig 1. Showing a clustered image

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Advantages
1) Fast, robust and easier to understand.
2) Relatively efficient: O(tknd), where n is # objects, k is # clusters, d 23 is # dimension of each object, and t is # iterations. Normally, k, t, d << n. 3) Gives best result when data set are distinct or well separated from each other.

Module 3: *FEATURE EXTRACTION USING GREY LEVEL COOCCURRENCE MATRIX*

The Gray Level Co-occurrence Matrix (GLCM) and associated texture feature calculations are image analysis techniques. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity (a.k.a. image texture) at the pixel of interest. The matrix is created as follows: Let s be the sample under consideration for the calculation. Let W be the set of samples surrounding sample s which fall within a window centered upon sample s of the size specified under Window Size. Considering only the samples in the set W, define each element i, j of 24 the GLCM as the number of times two samples of intensities i and j occur in specified Spatial relationship (where i and j are intensities between 0 and Number levels-1). The sum of all the elements i, j of the GLCM will be the total number of times the specified spatial relationship occurs in W.

• Make the GLCM symmetric
• Make a transposed copy of the GLCM

This produces a symmetric matrix in which the relationship i to j is indistinguishable for the relationship j to i (for any two intensities i and j). As a consequence the sum of all the elements i, j of the GLCM will now be twice the total number of times the specified spatial relationship occurs in W (once where the sample with intensity i is the reference sample and once where the sample with intensity j is the reference sample), and for any given i, the sum of all the elements i, j with the given i will be the total number of times a sample of intensity i appears in the specified spatial relationship with another sample.

1. Normalize the GLCM
2. Divide each element by the sum of all elements. The elements of the GLCM may now be considered probabilities of finding the relationship i, j (or j, i) in W. Calculate the selected Feature. This calculation uses only the values in the GLCM.

Energy, Contrast, Homogeneity, Correlation, Shade or 25, Prominence The sample s in the resulting virtual variable is replaced by the value of this calculated feature.

Module 4: *TRAINING AND CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK*

The ANNs consist of many connected neurons simulating a brain at work. A basic feature which distinguishes an ANN from an algorithmic program is the ability to generalize the knowledge of new data which was not presented during the learning process. ANN is a parallel distributed processor that has a natural tendency for storing experiential knowledge. They can provide suitable solutions for problems, which are generally characterized by nonlinear ties, high dimensionality noisy, complex, imprecise, and imperfect or error prone sensor data, and lack of a clearly stated mathematical solution or algorithm. A key benefit of neural networks is that a model of the system can be built from the available data. Image classification using neural networks is done by texture feature extraction and then applying the back-propagation algorithm.

IV. RESULT AND DISCUSSION

The output of the process is list of numpy array within which we have mean, variance and standard deviation of the training images. These values are used to train the neural network. We tested around 100 images form dermis images data set. We obtained an accuracy of about 85%.

Fig 2. Statistic values of training images

V. CONCLUSION AND FUTURE ENHANCEMENT

In this project, we analyzed the images of skin regions of cancer affected part. By analyzing images from DERMIS dataset, we studied the difference between melanoma and nevus, and also we studied the correlation between the two types. In this work, we also discovered ways to improve the accuracy of detection mechanism. The result can be shown using the interface and several remedies can be given to dermatologists that include assistance for the doctors.

Future work should explore to develop a progressive web application (PWA) that gives an easier user interface (UI) to make this usable for everyone. We can also improve the algorithms and computing methods to increase calculation speed and to analyze more than one image at a time.

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