Extraction of Structural And Textural Features By K-Means Clustering For The Detection of Skin Diseases

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Abstract- *Melanoma is a type of cancer that mostly starts in pigment cells (melanocytes) in the skin. While curable with early detection, only highly trained specialists are capable of accurately recognizing the disease. As expertise is in limited supply, automated systems capable of identifying disease could save lives, reduce unnecessary biopsies, and reduce costs. In this paper we propose a dual stage approach which effectively combines Computer Vision on clinically evaluated histo pathological attributes for accurate detection of melanoma and other skin diseases. The dual stage approach deploys the combination of two types of features namely Structural features and Textural features. In the first stage, the image of the skin lesion is subjected to various kinds of pre-processing techniques that yields a comparatively high image classification accuracy , namely image acquisition, color conversion, filtering and hair removal, contrast enhancement and image quality assessment .This stage is followed by structural and textural feature extraction by segmentation using clustering method. The second stage involves the use of algorithms to identify diseases based on the histo-pathological attributes observed on analysing the skin. Such a deployment yields a high accurate type of classification of the melanoma stages and any other skin disease. We also aim at the concept of using any type of skin lesion image irrespective of asymmetry, border, color and diameter and reducing the computational complexity of classification by processing the structural and textural features using K means clustering method.*

Keywords- Melanoma, Structural features, Textural features, median filter, Gray scale conversion, Adaptive histogram, K-means clustering.

I. INTRODUCTION

Skin is the layer of usually soft, flexible outer tissue covering the body of a vertebrae animal, with three main functions: protection, regulation, and sensation. Melanoma is a type of cancer that mostly starts in pigment cells (melanocytes) in the skin. Skin cancer is one of the most common worldwide malignancy. It has been found that over the past three decades, the people diagnosed as skin cancer is more than those diagnosed as all other cancers combined. Malignant melanoma is a kind of high-risk deadly skin cancer. Early detection of malignant lesions has great significance for helping the clinicians to improve the chances of survival. Because of the visual similarities of some lesion types, correct diagnosis is a challenging task for clinicians, and is largely dependent on the experience

One easy way to remember common characteristics of melanoma is to think alphabetically – the ABCD's of melanoma. ABCD stands for **asymmetry, border, color, diameter**. These four characteristics have proven to be highly instrumental in determining the type of disease worldwide but has not given an accurate result in the centuries.

These are the characteristics of skin damage that doctors look for when diagnosing and classifying melanomas. Melanoma is often **asymmetrical,** which means the shape isn't uniform. Non- cancerous moles are typically uniform and symmetrical in shape. Melanoma often has **borders** that aren't well defined or are irregular in shape, whereas non-cancerous moles usually have smooth, well-defined borders. Melanoma lesions are often more than one **color** or shade. Moles that are benign are typically one color. Melanoma growths are normally larger than 6mm in **diameter,** which is about the diameter of a standard pencil. The difference between a normal skin lesion and a melanoma skin lesion based on the ABCD rule from the National Cancer Institute is depicted in figure 1.

Treatment is dependent on the specific type of cancer, location of the cancer, age of the person, and whether the cancer is primary or a recurrence. For a small basal-cell cancer in a young person, the treatment with the best cure rate (Mohs surgery or CCPDMA) might be indicated.

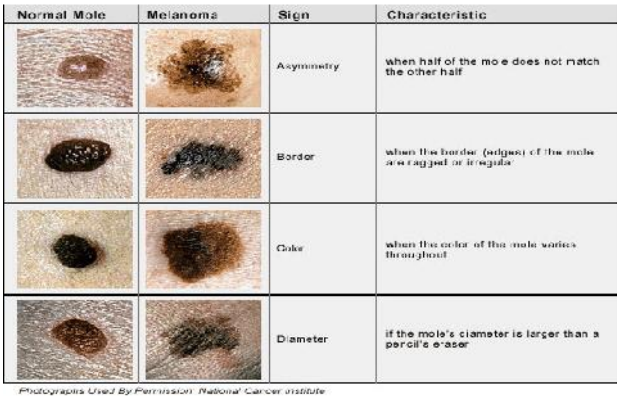

Fig:1 Difference between a Normal skin lesion and Melanoma skin lesion based on ABCD Rule.

Machine learning (ML) methods have shown their advantages in detecting key features and patterns from complex datasets, thus are suitable to perform classification, prediction or estimation tasks .In recent years there is growing trend on the application of ML methods as an aid to accurate and automated cancer diagnosis and detection. The application of ML techniques has significantly improved the accuracy of cancer prediction by 15% of 20% over the past decades.
The main objectives of this paper is to predict skin cancer using the dermatoscopic images from classification learner app, to obtain high accuracy for all types of skin images, to obtain low computational complexity, and to predict any other type of skin disease other than skin cancer.

II. LITERATURE SURVEY

In the literature, several researchers have focused on developing CAD systems for skin cancer detection. In hospitals, to detect the melanoma tissues, patients generally undergo a skin examination using the skin surface microscopy techniques commonly known as Dermoscopy. To measure the severity of skin deformation, physicians often use scoring methods such as the ABCD rule or the 7-point checklist for diagnosis and detection of melanoma.

As Image processing techniques, the contributions of different papers in the literature are in image preprocessing, segmentation, feature extraction and/or classification. For preprocessing of melanoma images, many methods proposed in the literature focused on hair removing and contrast enhancement. Once such methods, named Dullrazor, was introduced by Lee et al. to remove hair and image artefacts. It is one of the most widely known software in dermoscopic images.

Once the preprocessing step is completed, the next challenging task is the segmentation of melanocytic lesions from the processed images. It refers to separate an image into disjoint homogeneous regions respecting some properties such as luminance, colour and texture. This procedure is detailed in Celebi et al. and completed in , where the authors classified several methods of image segmentation explored in the literature into different categories such as histogram thresholding, clustering, edge based etc. They also compared the recent border detection methods (50 methods), and concluded that half (25/50) of them use smoothing filters, and those based on thresholding are inherently robust against noises. The authors noted that two methods, clustering (19/50) and thresholding (18/50), are the most popular segmentation methods.

The feature extraction step plays a crucial role in CAD systems, because the classification and diagnosis depends on the types of features extracted and their discriminating power. There are several feature extraction methods in skin cancer research as in , where the authors used the idea of the Asymmetry, Border, Color, Diameter, Evolving (ABCDE) rule for extracting the image's features from the regions of interest (ROIs). In this rule, A is asymmetry, B is border, C stands for colour, D is diameter and E is elevation or evolving (less used in clinical treatment).

Classification is the last step in the typical work-flow of computerised analysis PSL images. The classification performance is often measured in terms of accuracy, sensitivity and specificity. The computation of these metrics is mostly used to compare the results. The most used classification and often explored by radiologist on ABCD criteria is scoring system by thresholds, where the score is computed following the value and the weight attributed to each feature.

III. EXISTING SYSTEM

Deep learning methods have made some achievements in the automatic skin lesion recognition, but there are still some problems such as limited training samples, too complicated network structure, and expensive computational costs. Considering the inherent power-efficiency, biological plausibility and good image recognition performance of spiking neural networks (SNNs), malignant melanoma and benign melanocytic nevi skin lesions classification is performed using convolutional SNNs with unsupervised spike-timing-dependent plasticity (STDP) learning rule.

In order to evaluate the performance of the STDP-based convolutional SNNs on the skin lesion classification, the data from the International Skin Imaging Collaboration (ISIC)

2018 Challenge was used, which is an international effort to automatic skin lesion analysis towards melanoma detection, including lesion segmentation, dermoscopic feature extraction and lesion classification.

OVERVIEW OF THE METHODS:

The method mainly consists of three parts, namely skin lesion image data preprocessing, feature extraction based on spiking neural networks, and skin lesions classification using SVM classifier. The SNNs are similar to the networks of Kheradpisheh, which include a DOG encoding layer, three convolutional layers (Conv1, Conv2 and Conv3), and three pooling layers (Pool1, Pool2 and Pool3). The DOG filter is applied to convert the preprocessed skin images into spikes using the intensity-to-latency coding scheme. Convolutional layers and pooling layers are all consisting of integrate-and-fire (IF) neurons. Each convolutional layer learns features from its input by STDP learning rule, in combination with WTA weight updating strategy and lateral inhibition mechanism. Different to, in this work, the final global maximum pooling layer (Pool3) is replaced with a feature selection layer in order to improve the classification performance of the SNNs. The outputs of feature selection layer are then used to make the skin lesion classification by SVM classifier.

Data preprocessing is used to remove the hairs or noises in the raw images. Three preprocessing methods are used which are hair deleting, media filter and global contrast normalization. Many images in the ISIC dataset have a lot of hairs which affects the classification accuracy. Hair deleting is implemented by using an algorithm called DullRazor, which was proposed by Lee et al. and used to preprocess skin images. The DullRazor can remove hairs effectively, and also additional noises by using DOG Filtering. Finally, global contrast normalization was used to eliminate the effects of different light conditions on the pixel values of the images. It works by subtracting the mean of the intensities in the image to each pixel.

The features extracted by the convolutional layers in the convolutional SNNs are to some extent redundant (including irrelevant features). Kheradpisheh et al. used a global maximum pooling to compress input information and remove the redundancy. After the global pooling, there is only one output value for each feature map, which represents the most prominent feature of this feature map. These output values are then used to classify the input prototypes by SVM classifier. However, when classifying images with very high similarity, it is very likely that the global maximum pooling might filter some diagnostic but not the most prominent features, which will affect the classification result of the classifier. Therefore, to improve classification accuracy univariate feature selection is used based on chi-square test to replace the global maximum pooling in order to select more diagnostic features, while reducing redundancy.

When data are unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The support-vector machine algorithm, created by Hava Siegelmann and Vladimir Vapnik applies the statistics of support vectors, developed in the support vector machines algorithm, to categorize unlabeled data, and is one of the most widely use clustering algorithms in industrial applications.

The main objective of this paper is to develop an efficient method which classifies skin lesion images. To achieve high classification accuracy, fusing the outputs of the classification layers of four different deep neural network architectures has to be performed. For this kind of approach we have to train model many time and fine-tune them. Both are very time consuming procedures, so efficient implementations are also highly recommended because of the limited computational resources and the vast amount of training data.

IV. PROPOSED SYSTEM

In this paper, the concept of fusion of both structural and textural features for the classification of skin cancer and other skin diseases is proposed and and the detection and classification accuracy is obtained using classification learner app. This is performed in three stages namely Image preprocessing , Feature Extraction (Both structural and textural) by segmentation and Classification.

The results of the above steps are used to predict the stage and severity of the cancer and skin disease. The colour image containing the dataset of several skin types are converted to gray scale image to avoid any illuminations from environmental. The noise from the image is removed by using a median filter for high accuracy. Edge detection is performed using edge detector to eliminate unwanted areas and only the affected region is highlighted. A Convolutional neural network is deployed to extract the features. The structural and textural features are segmented and the result is viewed in classification learner app.

In the current work, a new approach for discrimination of melanoma lesions using multiresolution analysis such as wavelet and curvelet coefficients, combined with local binary pattern (LBP) operator applied on dermoscopic images has been explored. The developed approach uses the fusion of different features extracted from various operators. The structural features are obtained from multiresolution analyses (wavelet and curvelet coefficients) which are used to discriminate the structures as borders, dots and streaks. On the other side, the textural features computed by LBP operator are used to discriminate the local variation of colours, the pigment network etc. Later, these features are fused in multiple combinations to investigate the influence of each combination in the performance of melanoma detection.

The image of the skin lesion is subjected to various kinds of pre-processing techniques that yields a comparatively high image classification accuracy , namely image acquisition, color conversion, filtering and hair removal, contrast enhancement and image quality assessment .This stage is followed by structural feature extraction by segmentation using clustering method.

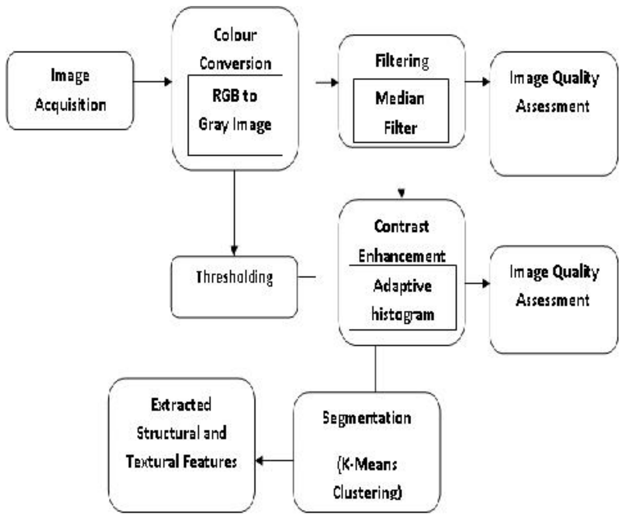

Fig 2: Flow Diagram of the Proposed System

IMAGE DATA PREPROCESSING

The Image data preprocessing is the first and foremost step to classification of any cancer or skin disease. Pre-processing is a common name for operations with images at the lowest level of abstraction — both input and output are intensity images. These iconic images are of the same kind as the original data captured by the sensor, with an intensity image usually represented by a matrix of image function values (brightness's). The aim of pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing, although geometric transformations of image are classified among pre-processing methods here since similar techniques are used.

The five stages of **Image preprocessing** deployed in the proposed system are as follows:

- ✓ Image Acquisition
- ✓ Colour conversion from RGB to gray scale image
- ✓ Filtering the noise using Median filter
- ✓ Contrast Enhancement using Adaptive Histogram Equalization
- ✓ Image quality assessment

a. Stage 1: Image Acquisition:

In this project, the input image taken here is the colored image (RGB Image) of the skin lesions samples obtained from the ISIC 2020 dataset .The image can be an unlabelled dataset of any type, shape, colour and appearance. ISIC has developed and is expanding a public archive containing the largest publicly available collection of quality controlled dermoscopic images of skin lesions.

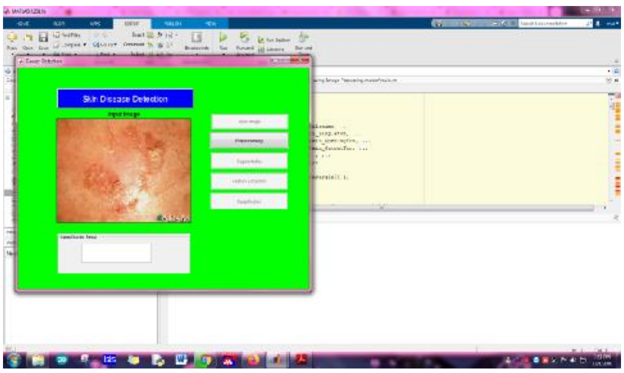

Fig 3: Result of Image Acquisition

b. Stage 2: Colour Conversion From RGB To Gray Scale Image:

In digital photography, computer-generated imagery, and colorimetry, a grayscale or greyscale image is one in which the value of each pixel is a single sample representing only an amount of light, that is, it carries only intensity information. Grayscale images, a kind of black-and-white or gray monochrome, are composed exclusively of shades of gray. The contrast ranges from black at the weakest intensity to white at the strongest.

Hence, the acquired RGB image is converted to a grayscale image to obtain an uniform spectacle of dataset unaffected by any illumination or atmospheric parameters such as humidity, dust etc and is represented in the form of Gray Level Coocurrence Matrix(GLCM).

Gray Level Coocurrence Matrix (GLCM):

Texture analysis aims in finding a unique way of representing the underlying characteristics of textures and represent them in some simpler but unique form, so that they can be used for robust, accurate classification and segmentation of objects. Though texture plays a significant role in image analysis and pattern recognition, only a few architectures implement onboard textural feature extraction. In this paper, Gray level cooccurrence matrix is formulated to obtain statistical texture features. A number of texture features may be extracted from the GLCM. The following four measures provide high discrimination accuracy required for motion picture estimation.

Correlation:

It passes the calculation of the correlation of a pixel and its neighbor over the whole image means it figures out the linear dependency of gray levels on those of neighbouring pixels. On behalf a perfectly positively or negative correlated image, the correlation value is 1 and -1.On behalf of constant image its value is NaN..Range=[-1,1] and the formula is

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$$

Contrast:

It passes the calculation of the correlation of a pixel and its neighbor over the whole image means it figures out the linear dependency of gray levels on those of neighbouring pixels. On behalf a perfectly positively or negative correlated image, the correlation value is 1 and -1.On behalf of constant image its value is NaN..Range=[-1,1] and the formula is

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij} (i-j)^2$$

Energy:

Since energy is used for doing work, Thus orderliness. It makes use for the texture that calculates orders in an image. It gives the sum of square elements in GLCM. It is fully different from entropy. When the window is proficient orderly, energy value is high .The square root of ASM(Angular Second Moment) texture character is used as Energy. Its range is [0 1].Since constant image its value is 1.The equation of energy is

$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2$$

Homogenity:

In short term it is going by the name of HOM. It passes the value that calculates the tightness of distribution of the elements in the GLCM to the GLCM diagonal. For diagonal GLCM its value is 1 and its range is [0,1].Opposite of contrast weight is homogeneity weight values, with weight decreases exponentially loose from the diagonal. The weight employed in contrast is (i-j)^2 and in homogeneity ,it is 1/1+(i-j)^2.The equation is

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2}$$

where:

P_{ij} - Element i,j of the normalized symmetrical GLCM
N - Number of gray levels in the image as specified by Number of levels in under Quantization on the GLCM texture page of the Variable Properties dialog box.

c. Stage 3: Filtering The Image Noise Using Median Filter:

The resulting gray scale image is given as an input to the median filter to remove the noise present and to improve the results of later processing. The Median Filter is a nonlinear digital filtering technique, often used to remove noise from an image or signal. 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 (but see discussion below), also having applications in signal processing.

Median filters are useful in reducing random noise, especially when the noise amplitude probability density has large tails, and periodic patterns. The median filtering process is accomplished by sliding a window over the image.

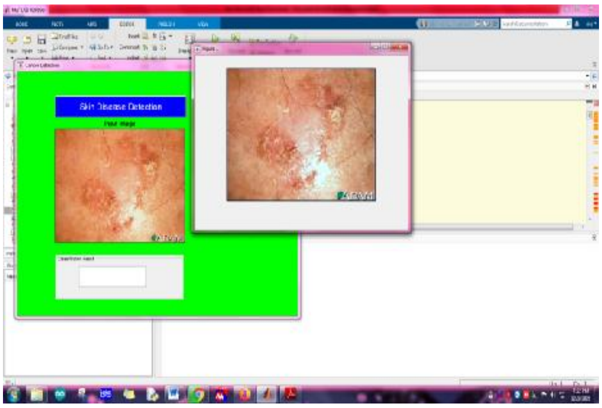

Fig 4: Result of Color conversion and Median Filtering

d. Stage: 4 Contrast Enhancement Using Adaptive Histogram Equalization Technique:

The resulting image from the previous stage is applied to a contrast enhancement technique.The method used in the existing system is ordinary histogram equalization. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image.

Fig 5: Result of Contrast Enhancement- Adaptive Histogram Equalization

e. Stage 5: Image Quality Assessment:

Measurement of image quality is important for many image processing applications. Image quality assessment is closely related to image similarity assessment in which quality is based on the differences (or similarity) between a degraded image and the original, unmodified image. There are two ways to measure image quality by subjective or objective assessment. Subjective evaluations are expensive and time-consuming. It is impossible to implement them into automatic real-time systems.

STRUCTURAL & TEXTURAL FEATURE EXTRACTION BY SEGMENTATION USING K MEANS CLUSTERING METHOD:

The next stage is to extract the structural and textural features of the skin lesion image by segmentation .The structural features are represented in terms of energy, entropy, mean, Std, maximum, moment and homogeneity. In this phase the segmentation process is done without using convolutional networks. Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels).

Clustering analysis can be done on the basis of features where we try to find subgroups of samples based on features or on the basis of samples where we try to find subgroups of features based on samples. We'll cover here clustering based on features. Clustering is used in market segmentation; where we try to find customers that are similar to each other whether in terms of behaviors or attributes, image segmentation/compression; where we try to group similar regions together, document clustering based on topics, etc.

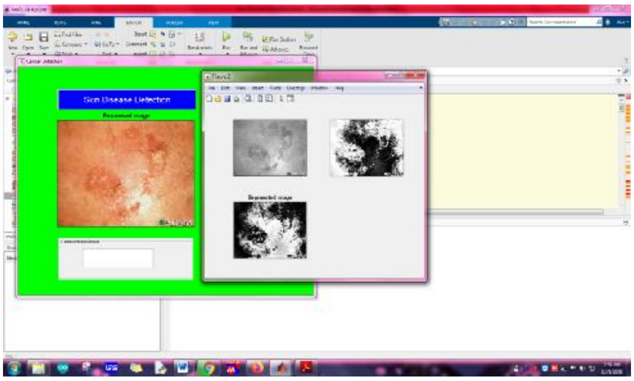

Fig 6: Results of Feature Extraction by K means Clustering (Segmentation)

K-Means Clustering Algorithm :

The K-means algorithm is an iterative technique that is used to partition an image into *K* clusters. The basic algorithm is

Step 1: Pick *K* cluster centers, either randomly or based on some heuristic method, for example K-means++
Step 2: Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
Step 3: Re-compute the cluster centers by averaging all of the pixels in the cluster
Step 4: Repeat steps 2 and 3 until convergence is attained (i.e. no pixels change clusters)

In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. *K* can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of *K.*

V. RESULTS AND DISCUSSION

The image preprocessing and extraction of structural and textural features by segmentation has been performed. The various stages of image preprocessing namely Image acquisition, Colour conversion, median filtering , contrast enhancement using AHE and image quality assessment has been implemented. The techniques that yield comparatively high classification accuracy such as the use of a median filter for removing noise, Adaptive histogram Equalization technique for contrast enhancement, Gray Level Cooccurence matrix for color conversion has been used for the detection of stages of melanoma and skin diseases. The Structural and textural features have been extracted individually by segmentation using clustering method for the detection of skin disease. The simulation is performed using MATLAB software.

VI. CONCLUSION

Since the need for early detection of melanoma is on demand for life saving strategies, it could be more convenient if the accuracy of the classification is increased so that it would be time saving and effective. This paper presents the stages of skin lesion processing and classification of Melanoma and other skin diseases accurately by the fusion of structural and textural features and has the advantage of processing any type of skin image with high precision and specificity. The use of techniques like median filter for removing noise, Adaptive histogram Equalization technique for contrast enhancement, Gray Level Cooccurence matrix for color conversion and K means clustering method for Segmentation, reduce the computational complexity to a great extent thus making the classification easier and simpler. This could be applied in the field of dermatology by clinicians for accurate melanoma detection.

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