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Extraction of Skin Lesions from Non Dermoscopic Images Using Deep Learning

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ABSTRACT

Melanoma is among most forceful sorts of disease. In any case, it is exceptionally treatable if distinguished in its initial stages. Prescreening of skeptical blot and sores for threat is of awesome significance. Location should be possible by pictures caught by standard cameras, which are more best because of ease and accessibility. One critical stride in electronic assessment of skin sores is precise discovery of sore's locale, i.e. division of a picture into two districts as injury and typical skin. Precise division can be trying because of weights, for example, brightening variety and low difference amongst injury and sound skin. In this work, a technique in light of profound neural systems is proposed for precise extraction of an injury locale. The info picture is preprocessed and afterward its patches are encouraged to a convolutional neural system (CNN). The tracts are handled keeping in mind the end goal to allocate pixels to sore. A strategy for compelling choice of preparing tracts is utilized for more precise discovery of a sore's fringe. The yield division cover is refined by some post handling operations. The trial consequences of subjective and quantitative assessments exhibit that our technique can beat other best in class calculations exist in the writing.

Keywords: Convolution Neural Networks, Medical Image Segmentation, Deep Learning, Melanoma, Skin Cancer

I. INTRODUCTION

Skin lesion identification and its classification is one of the most significant areas of work in dermatology. Various kinds of skin diseases are represented by different texture and effect on the skin. However the default skin color, age group, gender and so on has different effects on appearance or lesions in the skin. Several image processing techniques have been proposed in the past for efficient skin tumor detection and classification in various medical applications including brain tumor, melanoma and so on. Skin cancer segmentation using image processing techniques mainly depends upon the difference in the textual appearance of the cancer or the abnormal region in comparison to normal skin. Therefore the difference in the texture appears different for people with brown skin, people with dark skin and so on. Therefore image processing techniques have not found to be accurate enough when the brown or the dark skin images are being processed. Due to this inherent limitation of segmentation based skin cancer detection, machine learning based techniques are being getting popular.

A machine learning based technique is one where a mathematical decision making system such as neural network or fuzzy logic system is trained with priory knowledge. Whenever a sample is provided to such a system, the system can classify this as normal or abnormal based on the past training. However as the skin cancer images(both dermoscopic and non-dermoscopic) are extremely high resolution it takes immense amount of processing time and processing resources to classify a very high definition image. Therefore ensemble learning and classification which are biologically inspired are getting popular. An ensemble based learning is one where instead classifying a particular sample with a strong classifier, a sample is classified by several weak classifier whose results are then convoluted in order to obtain the final classification result, such kind of techniques is also known as convolution neural network(CNN).

A CNN is a special form of multilayer perception feed forward neural network. All the pixels or block of pixels are to be given as input to mark them as normal or abnormal. Further once all the pixels are classified the abnormal pixels are connected in order to obtain a cancer region. As mentioned earlier classifying a high definition image pixel is extremely time consuming. A convolution neural network on the other hand offers subsequent image classification techinique. It is inspired by the visual receptor of the of the animals. For example animals like cats, dogs has visual system that response to even a point of changes in their vision. That change then stimulates there neuron.

In a CNN several perceptions parallel processes different pixels with a weak classification stratergy. Whenever there is a significant variation in the results of multiple neurons that result is marked as abnormal. This enables the parallel processing and therefore the efficiency of the extremely good without compromising on the processing speed.

II. SYSTEM ANALYSIS

A. Existing System

Most of the existing skin cancer detection technique are based on the color, texture and shape features. Generally the abnormalities in a skin surface have been detected and encircled followed by an estimation of the perimeter of there area then average color intensity and average color texture description is used and threshold based technique is used to recognize. However threshold based technique has got its limitation as the skin texture varies from one geographic region to another geographic region, one gender to another gender, one age group to another age group. Therefore machine learning based technique is much more suitable for skin cancer detection because such a technique can minimize the drawback associated with thresholding and misdetection. Hence in order to overcome this problems of the existing system we propose the machine learning based system assisted by advanced fuzzy based segmentation technique to improve the overall performance.

B. Proposed System

The proposed system can be defined as machine learning based skin cancer detection technique where first the skin region is segmented using advanced fuzzy based clustering technique.

The clustered image is then classified by neural network and KNN classifier based on the fractal feature and color correlogram feature which represent the high level color and texture dimension of the image.

III. METHODOLOGY

In this work we propose two different type of techniques to detect skin cancer.

1. Segmentation based technique
2. Machine learning based technique

In the segmentation based technique we perform a compilation between fuzzy c means segmentation based skin cancer detection and thresholding based skin cancer detection. In the machine learning technique we compare performance between neural network and k nearest neighbor classifier.

The overall methodology of the project can be explained in following ways

A. Scan a color skin image which may or may not contain traces of melanoma.

B. Preprocessing

In preprocessing step we perform averaging filter which acts as a low pass filter that smoothes the skin area as well as abnormal area. After smoothing we perform a HSV conversion to reduce the number of color image, by thresholding the HSV region we are able to detect the traces of melanoma. We also use fuzzy c means technique to first define two clusters followed by classifying each of the pixels to one of this clusters depending upon the distance from the center of the cluster. Thus the image is clustered into skin and non skin area which is nothing but the tumor area.

FUZZY C MEANS : The point of FCM is to discover bunch focuses (centroids) that limit difference capacities. So as to oblige the fluffy dividing method, the participation grid (U) is arbitrarily instated. In the initial step, the calculation chooses the underlying group focuses. At that point, in later strides after a few emphasess of the calculation, the last outcome unites to genuine bunch focus. Hence a decent arrangement of introductory bunch is accomplished and it is essential for a FCM calculation. On the off chance that a decent arrangement of introductory bunch focuses is picked, the calculation make less emphasess to locate the real group focuses. The Fuzzy C-Means calculation is an iterative calculation that discovers bunches in information and which utilizes the idea of fluffy participation.

Rather than allocating a pixel to a solitary group, every pixel will have diverse participation esteems on each bunch. The Fuzzy C Means endeavors to discover groups in the information by limiting a target work appeared in the condition beneath:

$$J = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{m}(X_i - C_j)^2$$

J is the goal work. After one emphasis of the calculation the estimation of J is littler than some time recently. It implies the calculation is focalizing or getting more like a decent partition of pixels into bunches. N is the quantity of pixels in the picture, C is the quantity of bunches utilized as a part of the calculation, and must be chosen before execution, is the enrollment table – a table of NxC sections which contains the participation estimations of every information point and each group, m is a fluffiness element (an esteem bigger than 1), xi is the ith pixel in N, cj is jth bunch in C and contrast between (xi - cj) is the Euclidean separation amongst xi and cj.

Calculation of fuzzy c implies strategy

The contribution to the calculation is the N pixels on the picture and m, the fluffiness esteem.

1. Introduce with arbitrary esteems in the vicinity of zero and one; however with the aggregate of all fluffy participation table components for a specific pixel being equivalent to 1 – as it were, the total of the enrollments of a pixel for all bunches must be one.
2. Figure an underlying incentive for J utilizing,

$$J = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{m}(X_i - C_j)^2$$

3. Ascertain the centroids of the bunches cj utilizing,

$$c_j = \frac{\sum_{i=1}^{n} u_{ij}^{i} |X_i|}{\sum_{i=1}^{n} u_{ij}^{i}}$$

4. Ascertain the fluffy participation table utilizing,

$$u_{ik} = \frac{1}{\sum_{i=1}^{n} \left(\frac{|X_i - C_j|}{|X_i - C_k|}\right)^{\frac{2}{m-1}}}$$

5. Recalculate J.
6. Go to step 3 until a ceasing condition reaches.

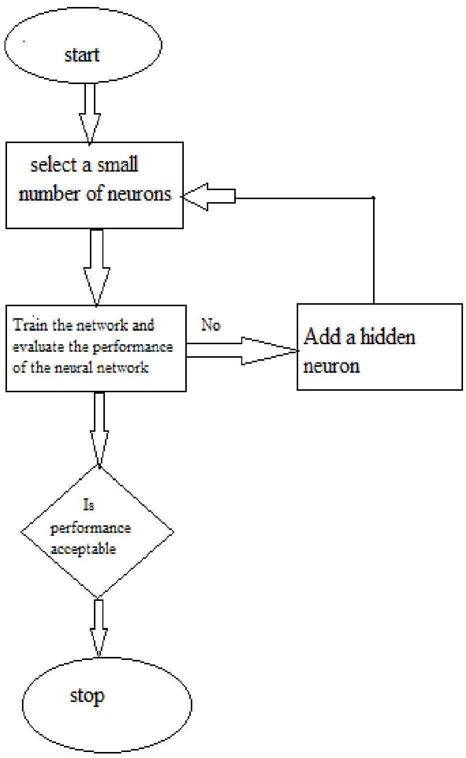


Figure 1 : Flow chart of fuzzy c means

C. Feature extraction

a) Fractal Feature

A fractal is a scientific set that shows a rehashing design shown at each scale. It is otherwise called extending symmetry or developing symmetry. On the off chance that the replication is precisely the same at each scale, it is known as a self-comparative example. Surface element extraction technique by Segmentation-based Fractal Texture Analysis or SFTA.

The extraction calculation comprises in breaking down the information picture into an arrangement of paired pictures from which the fractal measurements of the subsequent locales are registered with a specific end goal to portray fragmented surface examples.

SFTA removes surface elements from the grayscale picture I utilizing the SFTA calculation (Segmentation-based Fractal Texture Analysis). Restores a 1 by 6*nt vector D separated from the info grayscale picture I utilizing the SFTA calculation. The element route relates to surface data extricated from the info picture I. On the off chance that essential, the information picture is changed over to a grayscale picture with bit-profundity of 8. FINDBORDERS Returns a parallel picture with the districts' limits of the info picture I.

FINDBORDERS restores a paired picture with the areas' limits of the information picture I. The information picture I should be a twofold picture. The returned picture Im takes the esteem 1 if the relating pixel in I has the esteem 1 and no less than one neighboring pixel with esteem 0. Generally Im takes the value0. HAUSDIM restores the Haussdorf fractal measurement of a protest spoken to by a double picture. Restores the Haussdorf fractal measurement D of a protest spoken to by the paired picture I. Nonzero pixels have a place with a question and 0 pixels constitute the foundation.

b) Color Correleogram

A shading correlogram can likewise be said as correlogram delineates how the spatial relationship of set of match of hues changes with separation. By and large, a correlogram for a picture is only a table listed by various shading sets, where the dth passage for column (i,j)which indicates the Probabilistic of finding a pixel of shading j from a pixel of shading i at a separation d of the picture. An autocorrelogram catches the spatial connection between's the indistinguishable hues as it were. This data is a subset of correlogram and comprises of lines of the frame (i,j).

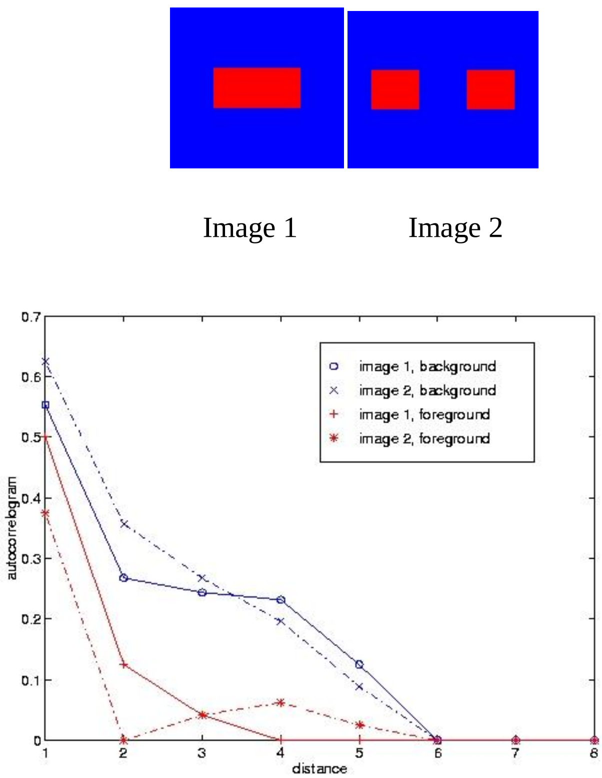


Figure 2: Two images with their autocorrelogram.

The highlights of the correlogram technique are:

i. It incorporates the spatial connection of hues

ii. It can likewise be utilized to depict the worldwide appropriation of the neighborhood spatial relationship of different hues if D is been as nearby. An extra favorable position lies in the capacity of our techniques to prevail with extremely coarse shading data.

D. Training and testing

In the training process we train the classifier k nearest neighbor or neural networks with the features extracted from already known normal and abnormal images.

E. Classification

In the classification we scan an unknown image of unknown class from user it is been preprocessed its features have been extracted and this features are given to the classifier based on this features classifies the image as normal or abnormal.

a) KNN

The k-closest neighbors calculation (k-NN) is a non-parametric technique utilized for characterization and relapse. In both cases, the info comprises of the k nearest preparing cases in the element space. The yield relies on upon whether k-NN is utilized for characterization or relapse:

• In k-NN characterization, the yield is a class participation. A protest is ordered by a dominant part vote of its neighbors, with the question being allocated to the class most regular among its k closest neighbors. On the off chance that k = 1, at that point the protest is essentially doled out to the class of that solitary closest neighbor.

• In k-NN relapse, the yield is the property estimation for the question. This esteem is the normal of the estimations of its k closest neighbors.

b) ANN

A manufactured neural system is an interconnected gathering of hubs, similar to the immense system of neurons in a cerebrum. Here, every roundabout hub speaks to a simulated neuron and a bolt speaks to an association from the yield of one neuron to the contribution of another.

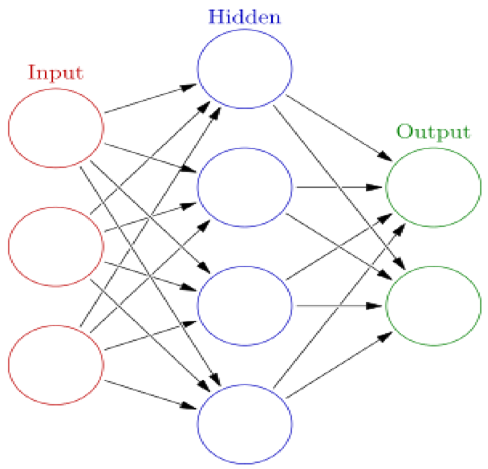


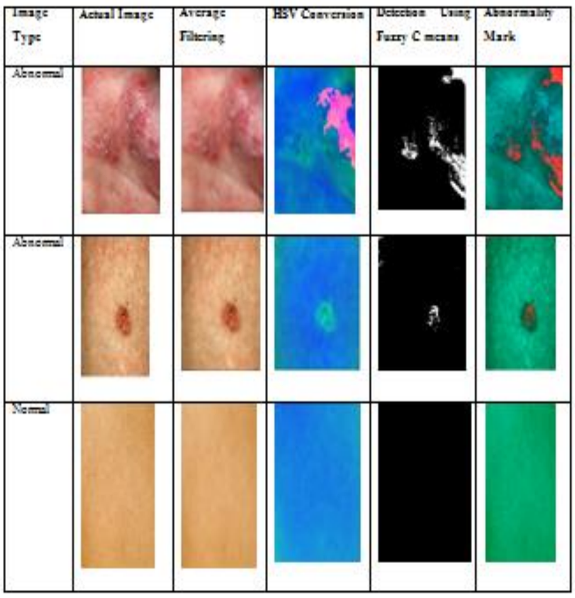
Figure 3 : ANN Classification

In the characterization we filter an obscure picture of obscure class from client it is been preprocessed its components have been extricated and this elements are given to the classifier in view of this elements orders the picture as ordinary or unusual.

F. Performance measure

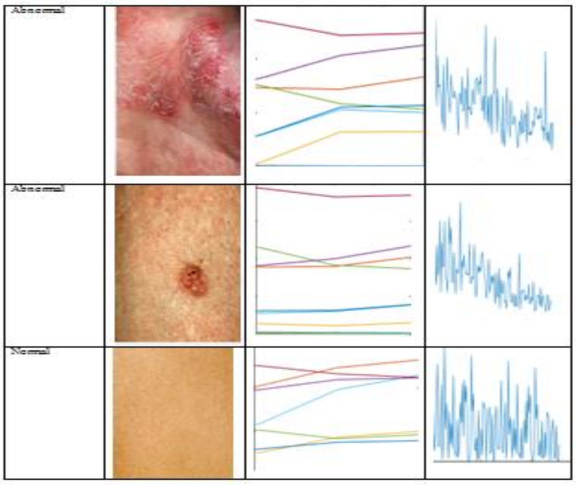
Once all the images have been classified we compare the performance of both the classifier by calculating the accuracy of detection. An accuracy can be defined as the number of correct detection with respect to total number of given image.

IV. RESULT ANALYSIS



(a) (b) (c) (d) (e)

Figure 4: Segmentation results (a)Actual input image (b) Smoothed image using Average filter (c) Applying HSV conversion (d) Detection of lesion using Fuzzy c means segmentation (e) Abnormality mark using Fuzzy C means



(a) (b) (c)

Figure 5: Feature Extraction results (a) Original image (b) Extracting Fractal features (c) Extracting Color Correlogram feature

(a) (b) (c)

Figure 6 : Testing Results (a) Test images (b) Testing using K-NN (c) Testing using ANN

V. CONCLUSION

Various forms of cancer diagnosis CAD(computer aided diagnosis) is becoming more popular due to more and more number of patients and not proportionate number of doctor. In a developing country like India where there are not sufficient numbers of doctor to diagnose or analyze patients record it is very important to have accurate and autonomous system diagnosis in place. Even though various kinds of skin cancer detection techniques have been proposed in past most of this are based on threshold based segmentation as the skin texture as well as cancer texture various depending upon the geographic, race, age, gender as well as the texture of the cancer also varies depending upon the benign or malignant stage of cancer. It is extremely difficult to appropriately detect cancer with such threshold based segmentation.

In order to overcome this limitation in this work we have proposed a novel machine learning based technique we represent a skin image using a color and texture based model where color is represented by an auto correlation system and texture is represented by fractal feature. Also to improve the performance we have introduced fuzzy based segmentation techniques that significantly improve the performance of the system. Our system not only helps detecting the cancer in a easy way but also can easily and efficiently classify the cancer.

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