

# FUSION OF STRUCTURAL AND TEXTURAL FEATURES FOR MELANOMA RECOGNITION

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**Abstract-**Melanoma is the deadliest form of skin cancer, which is considered one of the most common human malignancies in the world. Early detection of this disease can affect the result of the illness and improve the chance of surviving. The tremendous improvement of deep learning algorithms in image recognition tasks promises a great success for medical image analysis, in particular, melanoma classification for skin cancer diagnosis. Activation functions play an important role in the performance of deep neural networks for image recognition problems as well as medical image classification. In this paper, we show that a deep neural network model with adaptive piecewise linear units can achieve excellent results in melanoma recognition. Experimental results show that a convolutional neural network model with parameterized adaptive piecewise linear units outperforms the same network with different activation functions in the melanoma classification task. All experiments are performed using the data provided in International Skin Imaging Collaboration (ISIC) 2018 Skin Lesion Analysis towards Melanoma Detection.

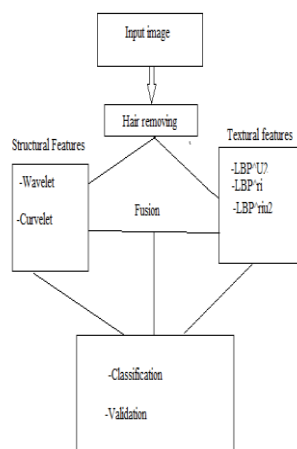
## 1.INTRODUCTION

Melanoma a type of skin cancer specifically known as malignant tumor of melanocytes. Melanocytes produce melanin the dark pigment, which handles color of skin. These cells moreover occur in the skin but are found in other parts of the body including eyes. Melanoma can originate in any parts of the body that contain melanocytes. It is the deadliest type of skin cancer, if it is not detected and cured in early stages. Nearly 160,000 new cases found every year. The chances of melanoma get more prominent due to an irregular operation of melanin-producing cells (melanocytes) that handles our skin color). Normally, skin cells grow in a controlled and orderly way; new healthy cells exert older cells out of your skin's surface, where they fall out and die off. In drastic scenario of DNA damage of some cells, newly generated cells may have uncontrolled growth and can form a mass of cancerous cells. Some leading factors behind DNA damage include environmental and genetic factors. After so much research and medical experiments, one can doubt that exposure to ultraviolet (UV) radiation from sun, tanning lamps and beds are leading causes of melanoma. UV light is not only a single reason for all varieties of melanoma especially in those cases, in which body parts being unexposed to sunlight. Exposure to ultraviolet (UV) rays remain a major risk factor for the most melanoma cases. People who receives lot of UV exposure from these sources are at a greater risk of skin cancer including melanoma. A nevus (mole) is a benign (non-cancerous). Moles does not present from birth in humans but start in children

and adults later. Moles does not create any problem but the person with many moles is more likely to develop melanoma. Dysplastic nevi (nevi is the plural of nevus) also termed atypical nevi often look like normal moles but also have some features of melanoma. They are often larger in size than other moles and shares abnormal shape or color. The lesions may appear on skin exposed to the sun as well as on skin that usually remain covered, such as the scalp or on the buttock. The risk of melanoma is ten times higher for white skin person. White with blond hair, blue or green eyes or fair skin that burns easily remains at increased risk. The risk of melanoma is greater when one or more first-degree relatives (brother, parent, sister, or child) had melanoma. Around ten percent of all people with Melanoma have a family history of the disease. The increased risk might be because of family lifestyle sharing frequent sun exposure or combination of factors. It may also be due to gene changes that run in a family. Gene anomalies have been found in anywhere from about ten to forty percent of families with a high rate of melanoma. Although melanoma is more likely to occur in older people, it is also found in the young generation. In fact, melanoma is prominent among younger than thirty (especially younger women). Men have a higher rate of melanoma compared to women overall, although this changes age by age. Before the age of forty the risk is higher for women, after an age of forty the risk is higher in men.

## II.EXISTING MODEL

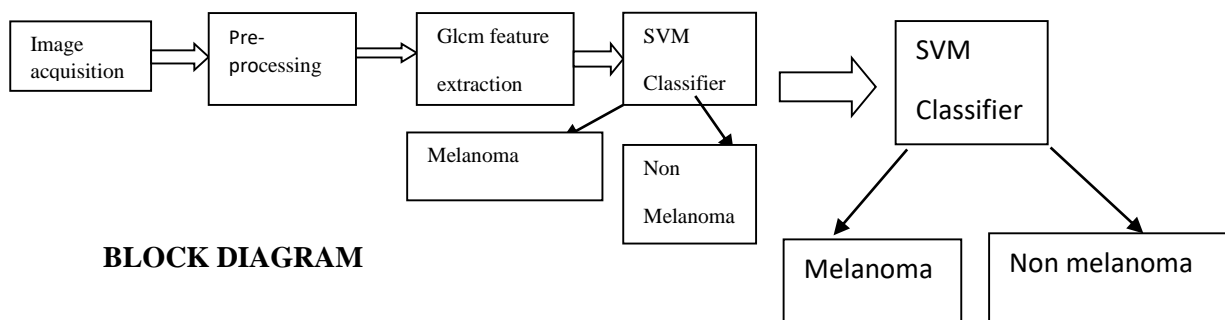
The feature extraction step plays a crucial role in CAD systems, because the classification and diagnosis depends on the types of features extracted and their discriminating power. There are several feature extraction methods in skin cancer research where the authors used the idea of the Asymmetry, Border, 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). A set of features are extracted by Celebi from multiple operators describing the shape such as asymmetry and compactness of the lesions, and colour features computing several statistical measures over channels and colour spaces. They also used textural features, where grey-level co-occurrence was employed. Multi-scale roughness descriptors were used by Clawson, Capdehourat and Arroyo and Zapirain, where the authors computed important statistical features as variance, Hessian matrix and entropy. They extracted Gaussian features using different values of  $\sigma$  and spectral texture features. To select the best features, a decision tree by means rule was implemented to obtain the 23 most significant features from a total of 80 extracted features.



**BLOCK DIAGRAM**

## III. PROPOSED MODEL

In order to improve the accuracy of feature extraction the algorithms used were converting to grey scale image, median filter. The RGB values of the images are extracted before converting it into a gray scale image. Sharpening filter is applied to the gray scale image in order to sharpen the details of the infected region. YCbCr was used to extract average colour code of the infected area from the binary image.



## GRAYSCALE CONVERSION:

A grayscale or greyscale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest. Grayscale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only two colors, black and white (also called bilevel or binary images). Grayscale images have many shades of gray in between. Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a given frequency is captured. But also they can be synthesized from a full color image; see the section about converting to grayscale.



Conversion of a color image to grayscale is not unique; different weighting of the color channels effectively represent the effect of shooting black-and-white film with different-colored photographic filters on the cameras.

Syntax

`I = rgb2gray(RGB)`

`newmap = rgb2gray(map)`

## **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:**

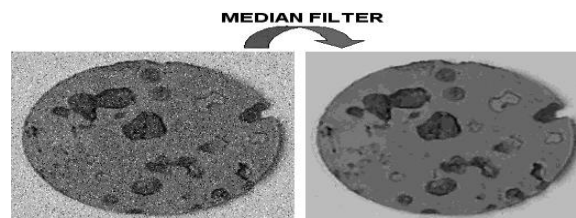
The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal. For 1D signals, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median.

## **2D MEDIAN FILTER PSEUDO CODE:**

```
allocate outputPixelValue[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 window[]
    outputPixelValue[x][y] := window[window width * window height / 2]
```

### **EDGE PRESERVATION PROPERTIES:**

Median filtering is one kind of smoothing technique, as is linear Gaussian filtering. All smoothing techniques are effective at removing noise in smooth patches or smooth regions of a signal, but adversely affect edges. Often though, at the same time as reducing the noise in a signal, it is important to preserve the edges. Edges are of critical importance to the visual appearance of images, for example. For small to moderate levels of (Gaussian) noise, the median filter is demonstrably better than Gaussian blur at removing noise whilst preserving edges for a given, fixed window size. However, its performance is not that much better than Gaussian blur for high levels of noise, whereas, for speckle noise and salt and pepper noise (impulsive noise), it is particularly effective. Because of this, median filtering is very widely used in digital image processing.



### **FEATURE EXTRACTION:**

In image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a features vector). This process is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

### **K-MEANS CLUSTERING:**

k-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. k-means clustering aims to partition  $n$  observations into  $k$  clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells. The problem is computationally difficult (NP-hard); however, there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually similar to the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. Additionally, they both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes. The algorithm has a loose relationship to the k-nearest neighbor classifier, a popular machine learning technique for classification that is often confused with k-means because of the  $k$  in the name. One can apply the 1-nearest neighbor

classifier on the cluster centers obtained by k-means to classify new data into the existing clusters. This is known as nearest centroid classifier or Rocchio algorithm.

## SUPPORT VECTOR MACHINE:

A support vector machine constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. Whereas the original problem may be stated in a finite dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mappings used by SVM schemes are designed to ensure that dot products may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function  $k(x, y)$  selected to suit the problem. The hyperplanes in the higher-dimensional space are defined as the set of points whose dot product with a vector in that space is constant. The vectors defining the hyperplanes can be chosen to be linear combinations with parameters  $\alpha_i$  of images of feature vectors  $x_i$  that occur in the data base. With this choice of a hyperplane, the points  $x$  in the feature space that are mapped into the hyperplane are defined by the relation:  $\sum_i \alpha_i k(x_i, x) = \text{constant}$ . Note that if  $k(x, y)$  becomes small as  $y$  grows further away from  $x$ , each term in the sum measures the degree of closeness of the test point  $x$  to the corresponding data base point  $x_i$ . In this way, the sum of kernels above can be used to measure the relative nearness of each test point to the data points originating in one or the other of the sets to be discriminated. Note the fact that the set of points  $x$  mapped into any hyperplane can be quite convoluted as a result, allowing much more complex discrimination between sets which are not convex at all in the original space.

## INFERENCE

To find better and more efficient ways to automatically detect early malignant melanoma using digital image pre-processing techniques. This focuses on the pre-processing stage, the image analysis of the tumor. The detection of melanoma cancer in early stage can be helpful to cure it.

## RESULT

We got the efficiency and the highest accuracy of above 82% as compared with the existing model. The investigate a svm classifier and the inference representation of the database used, which is important for the confidence of the obtained results. We can deduce by using the two sets of features(textural and structural).

## CONCLUSION

The work investigated in this article include SVM classifier to detect malignant melanoma from color images of skin. Some pre-processing step based on background illumination compensation and iterative dilation based noise removed is deployed to extract lesion features more accurately. The retrived result proves that supervised learning method based on SVM provides a promisable classification of a melanoma sample.



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