TEXTURE CLASSIFICATION USING CSTC-MEL IDENTIFICATION MODEL FOR DIAGNOSIS OF MELANOMA

Tammineni Sreelatha\textsuperscript{1}, M.V. Subramanyam\textsuperscript{2}, M. N. Giri Prasad\textsuperscript{3}

\textsuperscript{1}Research Scholar, Dept. of ECE, JNTUA, Ananthapuramu, AP, India
\textsuperscript{2}Principal, Dept. of ECE, Santhiram Engineering College, Nandyal, AP, India
\textsuperscript{3}Professor, Dept. of ECE, JNTUA, Ananthapuramu, AP, India

E-mail: \textsuperscript{1}tamminenisreelatha7@gmail.com, \textsuperscript{2}mvs.santhiram@gmail.com, \textsuperscript{3}mngiriprasad9@gmail.com

Corresponding Author: Tammineni Sreelatha

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Abstract

Texture in images can be utilized as a cue for different computer vision tasks as object identification and classification. This paper proposes CSTC-Mel Identification Model for texture classification, the feature representation which is low dimensional and training free, robust in nature for the texture description. The proposed technique is implemented in 3 phases such as ULL responses, feature computation, Feature encoding and the representation of image. Feature Computation is generated to categorize the texture structures and their connection by implementing linear and non-linear operators on the ULL responses of Gaussian Filter in the scale space, which is established based on steerable filters. Feature encoding through more than one level of thresholding or binary can be adopted to compute these feature computation into texture. Two encoding methods are designed which is robust in nature to the illumination changes and image rotation. The feature representation is explored to combine the discrete texture into the histogram representation. Our proposed model is tested on PH\textsuperscript{2} dataset. By comparing the experimental outcomes of proposed CSTC-Mel Identification Model with existing models, we can observe that the proposed CSTC-Mel Identification Model identifies the skin cancer with accuracy of 93.81%.

Keywords: Texture Classification, Steerable Filter, Gaussian Filter, Feature Computation, Feature Encoding.

I. Introduction

According to WHO (World Health Organization) [XXIII] both melanoma and non-melanoma issues are increasing over last few decades. Presently, 2-3 million of people are non-melanoma and 132,000 people are melanoma cases of skin cancer.
occur globally every single year. Melanoma is one of the most metastatic, malignant and hazardous form of SC (Skin Cancer) [IV]. It can be responsible for the main death, which is related to the SC (Skin Cancer) [XVIII]. The survival rate and curability of patient can be maximized if the melanoma can be identified at the earliest stage. Skin lesion is detected by the help of dermatologists utilizing the method, which is known as dermoscopy. This can be non-invasive process, which is utilized for the vivo observation of the skin lesion. The SCs can be categorized into 3 parts such as SCC, BCC and melanomas. Melanoma can be defined to be the disorder or condition, which affects the melanocyte cells thus maximizing the melanin synthesis [VIII-XVI]. This type of disorder can be categorized by the development of skin lesion and it differs in color, shape and texture. All three features are considered to be an eminent in the identification of melanoma.

Texture is an eminent feature, which recognizes the present object in any image[V]. The texture can be defined by the spatial distribution of the pixels in neighborhood image. The gray scale of spatial dependency can be introduced by GLCM and it can be utilized for the analysis of texture. The matrix of GLCM identifies [X] that how couple of pixels with the certain values happen in the image. The statistical measures are derived by GLCM matrix. The texture features represented as the spatial distribution of the gray tonal deviations within the identified part. In the given image, the neighboring pixel can be connected and the spatial values can be gained by redundancy among the neighboring pixel values. The color features can be signified by the help of color histogram in 6 color spaces such as OPP, RGB, HUE, HSV, CIE and LAB.

The texture in images is utilized as cue for different computer vision tasks such as object identification, segmentation and classification. In [XVII], the proposed model explores the variation of texture identification method using oriented Gaussian Filter with more than one orientation and scales. After getting filter responses at every single pixel location, KNN is utilized to define the regions with various textures. The modification of this algorithm is that only utilizing the filter responses magnitude at every single pixel location for defining the regions with various features via KNN. The outcomes are drastic changes in texture identification quality that compared to the original image.In this scenario, the feature representation has five desirable properties for the texture classification such as Discriminative, Efficient, Invariant, Low-dimensional and Insensitive.

This paper introduces CSTC-Mel Identification Model, called feature representation for the texture classification. In proposed methodology, first we calculate the ULL (Upper and Lower Limit) response and second Gaussian Filter at more than one scale. This can be accomplished by the ULL filtering which is recognized based on the steerable filters. The resulting ULL responses can be exactly rotation-invariant and very easy to implement. After that, we create the Feature computation by performing the non-linear and linear operator on ULL response to catch the discriminative texture information. The created feature computation can be used to categorize not only the local texture structure but also the 2nd order of curvatures which is derived from the 1st and 2nd order of image derivatives. Afterward, we quantize these feature computation into the discrete codes through
normal binary and more than one thresholding. Mainly, there are 2 types of feature encoding such as uniform and ratio encoder which can be designed for both the illumination changes and image rotation. Lastly, encodes the texture codes across the scales to construct the feature histogram that are combined to the form of the image descriptor. All given three phases, contribute low dimensional, robust and discriminative for the image descriptor.

The rest of the paper is organized in such a way that, section 2 gives the overview of the methods utilized for melanoma detection; section 3 provides the proposed CSTC-Mel Identification Model for texture classification. Section 4 presents results and discussion of experimental outcomes on various images for texture outcomes. Finally, the conclusions are presented in section 5.

II. Related work

There are many techniques for identification of melanoma in the dermoscopy images. Paper [VI], suggests the method in which the larger number of texture, border and color features are removed and then chosen as the input to KNN classifier. In paper [XXVII], the segmentation process has done utilizing the simple algorithm like adaptive thresholding. The GLCM matrix is utilized for removing texture feature in 4 various orientation angles. The color features are calculated by the color histogram in 6 different color-spaces. The classification is done by utilizing SVM-RBF for melanoma detection. In [XIII], the malignant melanoma was proven deadly SC, which can be more prevalent to the people between the certain ages. In paper [XII], the author has presented the failure to recognize and identify the disorders at earlier stage that can be very helpful since will lead to the development of lethal progressive melanoma [XIV]. These types of cases underline that the early recognition has been perceived the advantages to dermatologist. It cannot be deniable the early recognition of melanoma which is the paramount concern that has been proven to curtail frequent demise related with the malignancy. Early recognition of melanoma can’t be done by the bare eyes alone. For this, the dermatologist may apply computer-aided techniques like dermoscopy to give the clear vision and the magnification of skin morphology, which would invisible to naked eye. The technique known as computer-aided utilizes the dermoscopy algorithms to identify the condition of melanoma [VII].

Paper [XXII] introduces the portable library for the recognition of melanoma on the handheld devices because of BoF (Bag-Of-Feature) framework. They represented the time consuming and computational intensive of library such as image classification and the image segmentation that can attain the accuracy of speed of the execution similar to the desktop computer. These types of findings validated to execute the sophisticated biomedical of image applications on handheld devices and phones, which have the benefits of low cost and portability. Therefore, it can generate the important impact on health care of delivery as the assistive devices in remote area and under serves. Anyways, the system did not permit to take the images by smart phones. Afterwards in [XIX], various types of digital images have been examined based on pre-processing, image segmentation methods and the unsupervised image acquisition. Then, the FE can be applied on the segmented images. After that, the
graphical user interface was designed for the recognition of lesion. This paper [XXV], introduces the novel technique to separate the skin lesion via the concept of set level with respect to homogeneity level and MRF (Markov Random Field). The cluster property by local intensities was removed from image during level set and smoothing stages based on every single pixel to the every single point. Afterwards, the image can be segmented by MRF and the allocation of every single pixel of image to present classes that would be finally lead to the lesion separation from healthy skin.

In [III], the dermoscopy images are categorized into non-melanoma and melanoma by assuming the color and texture features of images. The well-known GLCM is utilized the textures features of the image. The color histograms are utilized to remove the color features in three different colors like RGB, OPP and HSV. The SVM is utilized for the classification process. The given methodology is examined by the metrics like specificity and sensitivity. Whereas in [XV], this paper introduces 2 main components of real-time non-invasive method of automated skin lesion analysis for melanoma initial recognition and the prevention. The first component is the real-time alert to help the users to prevent from skin burn caused by the sunlight; a new method is introduced to calculate time for the skin to burn. The second component is the analysis of automated image module that consists of lesion segmentation, classification, hair exclusion and detection, image acquisition. In [IX], the color and border based features are removed to be utilized in a classification module based on ANN (artificial neural networks). In paper [XX], the process of segmentation of skin lesion is implemented using GFAC model for accurate segmentation of the melanoma SC. In paper [XXIV], a comparison of different existing models is presented along with merits and de merits of each method.

III. CSTC-Mel Identification Model

This section presents our proposed detailed Color Shape Texture Classification (CSTC) - Mel Identification model, which is useful to recognize melanoma at initial stage.

III.i. Color Feature and Shape Feature Extraction

The two-feature extractions which are color and shape have been done in previous work. The color information is utilized by the medical experts in skin lesion classification. Thus, the feature of color has been utilized in CAD (Computer Aided Design) system. The popular features are utilized in dermoscopy analysis of the color statistics such as color variance and mean color. The Shape is the main source of information, which is utilized for recognition of object. Without shape feature extraction, the visual content of object shape cannot be identified. The images are not complete without identifying shape. Our proposed methodology for texture classification is described in next section.

III.ii. Texture Classification

The proposed technique explicitly encodes dual data within the image across the scale and feature spaces. The proposed technique is summarized into 3 phases such as ULL responses, feature computation, Feature encoding and the representation of image. Particularly, the given image can be convolved with the help of Gaussian
Filter to calculate the ULL responses at more than one scale. On the basis of these ULL responses, the set of Feature computation are created which can be rotationally invariant according to the steerable filters. The Feature computation can be computed into the DCT (Discrete Texture Codes) through the feature encoding. Lastly, textures are conjointly encoded across the scales to create more than one histogram that are connected to form feature representation.

Phase-1: It is the subsequent foundation phase and mainly utilized to eliminate the features of more than one scale rotationally invariant. These types of feature are insufficiently discriminative for the texture description.

Phase-2: It implements the feature computation to create discriminative feature for rotation invariant. Note that, it is not appropriate to concatenate directly all the feature computations over entire image as well as texture representation which leads to rotation-sensitive and higher dimensional image descriptor. Another technique is to utilize the feature computation as well as pixel-level-descriptor, which is followed by KNN to create the Texton-based texture descriptor. Furthermore, such type of technique needs learning phase and high KNN calculation.

Phase-3: It adopts Feature Encoding to get the discrete pixel to make the histogram based image features for the compact representation of feature. It can be specially intended by efficiently encode the produced texture codes across scales and features.

III.iia. The Upper and Lower Limit (ULL) Responses

LIDs (Local image derivations) consist of higher structural information that represents the huge potential in the analysis of texture. We utilize the Gaussian filter to calculate ULL responses in the space scale. Here, we discuss about these operators such as filtering of ULL. The main motive for representing ULL filtering is the multi-fold. The first filtering is to catch useful information, which is contained in 1st and 2nd order of differential structures at the scale ranges. The second filtering is to remove the local feature, which can be the rotation-invariant. The third filtering is to generate our methodology, which is very important to implement.

According to steerable filters [XXVI], the 1st and 2nd orientation derivative of Gaussian can be produced by taking linear mixture of many basic filters. The steerable filters can be utilized for the variety of containing oriented filters. Here, consider 2-D (Dimensional) circularly symmetric of Gaussian function as:

\[
G_f(a,b,\zeta) = \frac{1}{2\pi\zeta^2} e^{-\frac{a^2+b^2}{2\zeta^2}}
\]

(1)

Where, \( \zeta \) is denoted as the scale or SD (standard deviation). The 1st and 2nd of Gaussian derivative at arbitrary orientation \( \theta \) are:

\[
Gf_1^{\theta} = \cos(\theta)Gf_a + \sin(\theta)Gf_b
\]

(2)

And

\[
Gf_2^{\theta} = \cos^2(\theta)Gf_{aa} - \sin(2\theta)Gf_{ab} + \sin^2(\theta)Gf_{bb}
\]

(3)
Where, $G_{f_{aa}}$ and $G_{f_{a}}$ are the scale-normalized 1\textsuperscript{st} and 2\textsuperscript{nd} derivatives of $G_f$ along with $a\_axis$ and likewise $G_{f_{bb}}$, $G_{f_{ab}}$ and $G_{f_{bb}}$. We have excluded the arguments $(a, b, sd)$ for simplicity. These 5 basis filters are utilized in Equation (2) and equation (3) which are represented above.

Given the Image $\mathcal{I}$, we first calculate 1\textsuperscript{st} and 2\textsuperscript{nd} order of image derivatives by

$$D_\theta = G_{f_{\theta}} \ast \mathcal{I},$$
$$D_\phi = G_{f_{\phi}} \ast \mathcal{I},$$
$$D_{\theta\phi} = G_{f_{\theta\phi}} \ast \mathcal{I},$$
$$D_{\phi\theta} = G_{f_{\phi\theta}} \ast \mathcal{I},$$
$$D_{\phi\phi} = G_{f_{\phi\phi}} \ast \mathcal{I},$$

where $\ast$ is denoted as the convolution. Then, the first and second responses of Gaussian filter at the orientation $\theta$ are

$$J_{1}^\theta = G_{f_{1\theta}} \ast \mathcal{I} = \cos(\theta) D_a + \sin(\theta) D_y = \left(D_a^2 + D_y^2\right)^{1/2} \ast \sin(\theta + \Phi) \ (4)$$

Where, $\Phi = \arctan\left(\frac{D_a}{D_y}\right)$ and

$$J_{2}^\theta = G_{f_{2\theta}} \ast \mathcal{I} = \cos^2(\theta) D_{aa} - \sin(2\theta) D_{ab} + \sin^2(\theta) D_{bb}$$
$$= 0.5 \left(D_{aa} + D_{bb} + \left((D_{aa} - D_{bb})^2 + 4D_{ab}^2\right)^{1/2} \ast \cos(2\theta - \gamma)\right) \ (5)$$

Where, $\gamma = \arctan\left(\frac{2D_{ab}}{D_{bb} - D_{aa}}\right)$

Then, we can calculate the ULL responses in same way. $J_{1}^\theta$ denotes the upper value of over all $\theta$ is:

$$J_{1\text{up}}^\theta = \left(D_a^2 + D_y^2\right)^{1/2} \ (6)$$

The ULL values of $J_{2}^\theta$ over all $\theta$ are:

$$J_{2\text{up}}^\theta = 0.5 \left(D_{aa} + D_{yy} + \left((D_{aa} - D_{bb})^2 + 4D_{ab}^2\right)^{1/2}\right) \ (7)$$

And

$$J_{2\text{lower}}^\theta = 0.5 \left(D_{aa} + D_{yy} - \left((D_{aa} - D_{bb})^2 + 4D_{ab}^2\right)^{1/2}\right) \ (8)$$

Without the generality loss, let's revolve the image $\mathcal{I}$ of counter-clockwise nearby its midpoint by the help of $\alpha^\circ$ (arbitrary angle) and the rotation images are denoted as $\mathcal{I}'$. Here we consider the point $(a, b)$ in $\mathcal{I}$ that achieves ULL responses, which is well defined in Equations (6) – (8) via 1\textsuperscript{st} and 2\textsuperscript{nd} directional of Gaussian Filter at the angle of $\theta^\circ$.

Afterwards, the point $(a', b')$ in $\mathcal{I}'$ can also be obtained in the similar way of ULL responses via the directional derivative filter at the angle $(\theta + \alpha)^\circ$, which is ULL response for 2 corresponding points among the arbitrarily images that are exactly not variant.

III.b. Feature Computation

We would like to create the discriminative feature computation by taking into consideration of subsequent coding and encoding with achieved ULL responses.
In the end, we implement linear and non-linear operator on ULL responses to quantitatively categorize the structure of local texture and their connection. The FC (Feature Computation) is generated by:

1. The magnitude of gradient $m$, which is upper response of 1st directional of Gaussian Filter:
   \[ m = \mathcal{I} = (D_a^2 + D_b^2)^{1/2} \]  

2. The ULL difference $d$, which is the difference of ULL responses of 2nd directional Gaussian Filter:
   \[ d = \mathcal{I} = (D_{aa} - D_{bb})^2 + 4D_{ab}^2)^{1/2} \]  

3. The Index of shape $i$, which gives the quantitative measure of the local 2nd order of curve:
   \[ i = 0.5 - \frac{\pi}{2} \arctan \left( \frac{(\mathcal{I} + \mathcal{I}) - (\mathcal{I} - \mathcal{I})}{(\mathcal{I} + \mathcal{I})^2 + 4\mathcal{I}^2} \right) \]  

It is to be noted that, the index of shape can be initially described in the classical differential geometry and it can be derived from the surface of principle curves. For example the characteristic values $c_1$ and $c_2$ of $H$ Hessian matrix:

\[ H = \begin{bmatrix} D_a & D_{ab} \\ D_{ab} & D_{bb} \end{bmatrix} \]  

And

\[ i = \pi^{-2} \arctan (c_2 + c_1) * (c_2 - c_1)^{-1} \text{ (} c_1 \geq c_2 \text{)} \]  

The entire values of $i'$ in Equ (13) has been mapped to interval of $[0, XXIII]$ for the simplicity of subsequent-processing. The index of shape $i$ described over the finite interval can be quantitatively categorize different local second order of curves creating better choice for generating the features of discriminative computation.

4. The mix ULL ratio $r$ catches the connection information of 1st and 2nd order of differential structures. To generate the output that has less dynamic range, we utilize the function of arctangent as the rectifier.
   \[ r = \pi^{-2} \arctan \left( s, \frac{d}{m} \right) = \pi^{-2} \arctan \left( s, \frac{\mathcal{I} - \mathcal{I}}{\mathcal{I}} \right) \]  

Where $s$ represents the scale factor to modify the ratio of $m$ and $d$. The generated feature computation is denoted as $T = \{m, d, i, r\}$ have following things. Firstly, they are rotationally and compact invariant. This can be performed by executing non-linear and linear operator on the rotation-invariant of ULL responses $\mathcal{I}$ and $\mathcal{I}$ like linear mixtures of ULL responses to obtain $\{m, d\}$ whereas the non-linear combinations get $i$, $r$.

III.ii.c. Feature Encoding

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In this encoding, every single input symbol can be treated separately while generating the output. Here, we assume encoding as the feature computation into the discrete texture codes. For designing the better encoding, there are discriminative power and the computational efficiency as robustness to illumination and the robustness changes. These types of goals have two types of feature encoding through multi-level and simple binary, which can be designed by various feature properties.

For the feature computation \( \{m, d\} \), whose values are the non-negative interval, we acquire mean-value on the basis of binary ratio encoder \( E_1(\cdot) \):

\[
b = E_1(a) = \begin{cases} 
0, & \text{if } \frac{a}{v_a} > c \\
1, & \text{otherwise}
\end{cases} \quad (15)
\]

Where, \( a \in \{m, d\} \), \( c \) is the tuning parameter, and \( v_a \) is denoted as the mean value of feature computation of \( a \). Now, the utilization of \( v_a \) can be the robust to the image rotation. For feature computation \( \{i, r\} \) whose values can be in the range of \([0,1]\), then we assume the uniform encoding \( E_2(\cdot) \):

\[
b = E_2(a) = \begin{cases} 
0, & a \in [0, \Delta] \\
1, & a \in [0, 2\Delta] \\
\ldots \ldots \\
D - 1, & a \in [(D - 1)\Delta, 1]
\end{cases} \quad (16)
\]

Where, \( a \in \{i, r\} \), \( D \) is the level of encoder, and \( \Delta = \frac{1}{D} \) can be the step of encoding. The encoding levels for \( i, r \), represented by \( D \_i \) and \( D \_r \), aren’t essentially the similar, but both are related to feature dimension and texture discrimination. If the level of encoder \( D \_i \) and \( D \_r \) are too little, then encoding the feature code will be the discriminative of lacks and coarse. If it is too larger, then the resultants features of codes will be distort and tend to process of higher dimensional of the feature representation.

On the basis of above steps, the efficiency of computation can be attained by utilizing feature encoding. Meantime, the power of discriminative can be maintained by selecting the proper level of encoder \( D \) through more than one level of thresholding. Additionally, the rotation variance can be inherited from the set of feature \( T = m, d, i, r \) which is used in Equation (15) and (16).

III.ii.d. Feature Representation

We combine the created texture codes with histogram, which is based on feature representation. The simple way is to encode all the given texture codes at scales, however the resulting feature of histogram is very sparse and high dimensional, and may not be the discriminative. To deal with this issue, we introduce feature encoding to create more than one feature of histograms, after that concatenate histogram for the feature representation. As presented in figure 1, these feature encoding have robust discriminative power in describing the various local structures and curves. Additionally, the set of feature \( T \) provides corresponding information by employing both absolute amplitude values \( i.e \ (m, d) \) and values of relative ratio \(arel, r\). Lastly, feature subset \( i, r \), whose values are in range of \([0, XXIII]\), that provides itself to the normal uniform encoder, which is defined in Equation(16).
AS (Adjacent scale): the feature computation \(\{m, d, i\}\) are equally encoded across the 2 adjacent scales such as \((\varsigma_1, \varsigma_2), (\varsigma_2, \varsigma_3)\). For the pair of adjacent scale \((\varsigma_x, \varsigma_{x+1}) (x = 1, 2, ..., P_c - 1)\), the pixel value of AS \((a, b)\) in the image \(I\) can be calculated as:

\[
s_x(a, b) = \sum_{y=1}^{2} (D_i)^{y-1} b_i(a, b; \varsigma_{x+y-1}) +
\]

\[
(D_i)^2 \sum_{y=1}^{2} (D_d)^{y-1} b_d(a, b; \varsigma_{x+y-1}) +
\]

\[
(D_i)^2(D_d)^2 \sum_{y=1}^{2} (D_m)^{y-1} b_m(a, b; \varsigma_{x+y-1})
\]

(17)

Where, \(b_i(a, b; \varsigma_x), b_d(a, b; \varsigma_x)\) and \(b_m(a, b; \varsigma_x)\) are encoded the texture (with corresponds to the encoder levels \(D_i, D_d\) and \(D_m\)) for the feature \(i, d\) and \(m\) at scale \(\varsigma_x\).

FS (Full-Scale): the feature computation \(\{r\}\) is mutually encoded across all \(P_c\) scales \(\varsigma_1, ..., \varsigma_{P_c}\). The pixel value of full scale \((a, b)\) in the image \(I\) can be computed by:

\[
s_P(a, b) = \sum_{y=1}^{P_c} (D_r)^{y-1} b_r(a, b; \varsigma_y)
\]

(18)

Where, \(b_r(a, b; \varsigma_y)\) is represented as encoded texture for the feature \(r\) at scale \(\varsigma_y\) and the encoder level is \(D_r\).

Afterwards, \(P_c\) histogram feature \(\{H_x | x = 1, 2, ..., P_c\}\) can be constructed for the image \(I\):

\[
H_x(\ell) = \sum_{(a, b) \in \ell} u(s_x(a, b), \ell)
\]

(19)

Where \(\ell \in \{0, 1, ..., s_x\}\) \(s_x\) is represented as the upper value of \(s_x\) and

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\[ u\{g, h\} = \begin{cases} 1, & \text{if } g = h \\ 0, & \text{otherwise} \end{cases} \quad (20) \]

IV. Results and Discussion

The experiments are carried out using 400 dermoscopic images, which are combination of melanoma and non-melanoma. The proposed model is tested on the PH2 dataset [XXI] which consists of clinical diagnosis and the recognition of several dermoscopic and manual segmentation images. This dataset established as a benchmarking for research purpose. The experimental outcomes are performed in every single texture sample into the gray scale after that normalize to have standard deviation and zero mean. The process of normalization eliminates the global affine of illumination changes. Here, we utilize KNN-classifier for the texture classification.

IV.i. Texture Feature Extraction

The texture image shows the intensity of spatial organization and the color in image, it can be categorized in different way. Few of the techniques utilize the pixel statistic. The classifier model contains calculating the statistics of pairs of the neighboring pixel, Hessian matrix. This model has been developed and modified in several different ways. All three features are necessarily for initial detection of melanoma. The color and shape feature extraction are carried out in previous work. The texture feature extraction is classified into two parts such as melanoma and non-melanoma. Texture feature have been removed from gray image using Gaussian Filter. Here, we apply the non-linear and linear operators in ULL responses to quantitatively categorize the texture structures and their connection. The texture features computation can be generated on the basis of magnitude of gradient and ULL difference, which is shown in Figure 2 and Figure 3. The below given figure 2 and 3 defines the rotation invariance of feature computation. They are complementary and discriminative. The set of feature \( T \) encompass the information about first \((m)\) and second order \((d)\) of differential structures and combined both such as \( r \) in the scale space. Whereas, \( m \) denoted the magnitude of gradient and \( d \) denotes the ULL differences.

Melanoma

![Melanoma Images]
Fig. 2: Images of feature computation $m, d$. Figure (a) represents the original image of melanoma (b) represents the magnitude of gradient and (c) represents the ULL differences.

Non-Melanoma

Fig. 3: Images of feature computation $m, d$. Figure (a) represents the original image of non-melanoma (b) represents the magnitude of gradient and (c) represents the ULL differences.

IV.ii. Performance Metrics

In order to estimate the performance of proposed model, we utilize various performance metrics such as accuracy (A), precision (P), F-score (F) and specificity (S). The accuracy of proposed model can be classified using KNN classifier.

Accuracy is defined as the ratio of correctly observation to total observation in dataset and it is given by:

$$A = \frac{TP + TN}{TP + FP + FN + TN}$$

(21)
Precision is defined as the fraction of correct positive observation and it is given by:

\[ P = \frac{TP}{TP+} \quad (22) \]

F-Score is defined as the weighted average of recall and precision and it is given by:

\[ F = \frac{TP}{TP+FN} \quad (23) \]

Specificity is defined as the ratio of correctly predicted true observation and it is given by:

\[ S = \frac{TN}{TP+FP} \quad (24) \]

IV.iii. Comparative Analysis

The classifier outcome represents the values of various metrics of texture feature extraction. In this accuracy is 93.81, Precision is 92.31, F-score is 80.00 and Specificity is 98.75. In our previous work, the outcome of accuracy for color based feature extraction is 90.50, Precision is 83.87, F-score is 73.24 and Specificity is 96.88. Here, in the process of comparing the proposed model outcomes with existing system, we see that the accuracy of existing BWS based is 84.50, Precision is 61.54, F-score is 67.37 and Specificity is 87.90. Our proposed algorithm outcomes are much better than the existing algorithm. Below Table 1 represents the difference between our algorithm and existing algorithm values.

| Dataset          | Methods                              | Accuracy | Precision | F-score | Specificity |
|------------------|--------------------------------------|----------|-----------|---------|-------------|
| PH²[22]          | Madooei et al [XXIII]                | 76.50    | 47.67     | 63.57   | 71.43       |
|                  | Celebi et al. [XXIV]                 | 79.50    | 51.28     | 66.12   | 75.80       |
|                  | Madooei et al. [XXV] (BWS)           | 84.50    | 61.54     | 67.37   | 87.90       |
|                  | CSC-Mel Identification Model(color and shape) [XXVI] | 90.50    | 83.87     | 73.24   | 96.88       |
|                  | Proposed model (CSTC-Texture)        | 93.81    | 92.31     | 80.00   | 98.75       |

V. Conclusion

In this paper, we have presented the CSTC-Mel Identification model, for texture classification. The results are achieved by encoding and quantizing the Feature Computation derived from ULL responses of 1st and 2nd directional Gaussian Filter. The feature Computations is generated to categorize the texture structures and connection. Feature Encoding i.e., more than one level thresholding or binary is implemented to create the informative texture. The proposed CSTC-Mel Identification Model is more efficient and training free to implement. It is also robust.

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and low dimensional for the texture description. The accuracy of the CSTC-Mel identification model is 93.81% with a precision of 92.31%. Experimental results show that the proposed model is more efficient and robust than the existing model.

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