

Accuracy Assessment & Classification of Keratosis Skin Lesion Images using Feature Extraction & Classification Algorithms-LBP, LDP& HOG

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Abstract: *There are hundreds of human-affected skin diseases. The most severe skin disorders may have identical symptoms, so recognizing the distinctions between them is crucial. People should work closely with a dermatologist to identify and manage every skin disorder and insure it does not impact their lifestyle. Actinic keratosis (AK), that is also classified as solar or senile keratosis; is a pre-malignant crusty, thick skin area. It is a disorder of epidermal keratinocytes, induced by UV radiation upon the skin. While pre-cancerous in nature, they can develop into a form of skin cancer called carcinoma if left unaddressed. The other type of keratosis dealt within this paper is seborrheic keratosis, which are brown or black, thick, wart-like, waxy oval-shaped, slightly raised skin surfaces. The growths aren't damaging. Nevertheless, in some instances it can be impossible to differentiate a seborrheic keratosis from melanoma, which is a very dangerous form of skin cancer. Nevus (or moles) skin lesions are ones which are benign, where it may very rarely turn into melanoma skin cancer. In this article, along with techniques for extracting features (LDP [Local Directional Patterns], LBP [Local Binary Patterns] and HOG [Histogram of Oriented Gradients]), we have used an SVM classifier for the classification of Keratosis and also nevus skin photos. The LBP, LDP and HOG are means to extract features; these images are subsequently used for identification of derived features from these methods or algorithms and classified by the SVM (Support Vector Machine) classifier. For many of the classifications of keratosis and nevus skin images using these algorithms, we have obtained accuracy nearly above 80 %, whereby the LBP system together with the SVM classifier was the most powerful attribute extraction tool of the three with their polynomial kernel type. Using this algorithm-classifier, the main AK and nevus skin lesion images can be detected and diagnosed by the doctors in its early stage itself, thus helping save lives.*

Keyword: Keratosis, actinic, seborrheic, nevus, lesions, benign, pre-malignant, feature extraction, SVM, LBP, LDP, classification.

I. INTRODUCTION

Skin cancers usually ensue due to the abnormal cell development on the skin and has the tendency to disseminate throughout the human flesh[1].

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Basal-cell skin cancer (BCC), squamous-cell skin cancer (SCC) and melanoma are its three major forms [2], where this paper focuses on the types of Keratosis, where one of them, which is only a skin disease, develops into the SCC. Keratosis is keratin production on the skin, or mucous membranes that derive from keratinocytes, the epidermis' influential cell type. In specific, it may refer to Actinic, Seborrheic Keratosis, etc., where AK is a pre-malignant growth and SK is not [3]. Actinic keratosis (AK) is a specific category of skin lesion that typically signifies an early stage of squamous cell carcinoma (SCC) in situ[4][5]. Tumor development is typically affected by access to sunlight [6], genetic features, age, class, & type of skin. In regularly exposed body regions like nose, head, neck & limbs, AK lesions develop, because, not only the severity but also the persistent existence of exposure to sunlight is the major cause of AK progression. Thus its early diagnosis is crucial to avoid the likelihood of its development into SCC [7].



Fig 1: Actinic Keratosis affected skin lesions on a human hand and their lesion-based difference with the SCC.

Melanoma frequently fits a mild skin disorder, seborrheic keratosis (SK), which contributes to misdiagnosis. Therefore, detecting SK skin lesions is necessary to prevent triggering more anxiety or pressure [8].

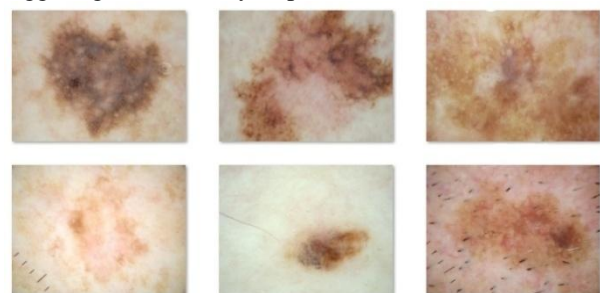


Fig 2: Shows some of the Seborrheic Keratosis skin lesion images.

Nevus (or nevi, if multiple) is a non-specific medical term for a noticeable, confined, recurrent skin or mucosal lesion [9]. A nevus is mild in most cases, and does not need medication. They occasionally become melanoma, or other skin cancers. For removal should be examined a nevus that shifts form, grows bigger or darkens.

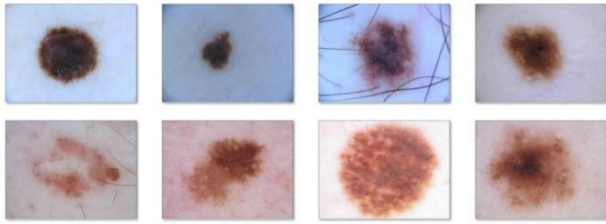


Fig 3: Depicts the input dataset images of nevus skin lesions

Despite its lack of human intelligence, a machine can collect details such as texture features, asymmetry – features that lie outside the normal scope of human-vision. For computer-vision dependent melanoma, the key steps are image processing of skin lesion pattern, image recognition algorithms extraction function and SVM detection from non-melanoma vegetative cell pictures. The approaches of extraction of functionality is based on the correct data. Geometry and Appearance-based approaches are 2 types of methods used in function extractions. The abstraction of the facial features minimizes the resources needed for the process, without losing relevant information. This allows to reduce obsolete data back to restricted analysis [10]. Global face descriptor (GFD) and local face descriptor (LFD) are two of the most widely employed types of representation of faces. The LFD typically separates the entire image into multiple distinct images and then removes the attributes, but in the case of GFD, using the complete image to extend a representation[11] in the proposed scenario, we use the LFD approach such as LBP to resolve the contextual trends within the different visual recognition processes[12][13]. The precision of the system relies on how the properties are derived from an image. For feature extraction purpose, we use the three-function extraction methods LBP[11][15], LDP [14] and HOG[16] and then employ the SVM classifier to achieve classification of the extracted features. Dataset of the skin lesion images of the 3 types of skin-conditions are used for assessment and teaching throughout this paper to measure the specificity or consistency of the picture distinguishing.

II. RELATED WORKS

In this work, we propose to classify the 3 types of skin conditions where 2 of them are types of keratosis and the other called nevus, which are usually benign skin lesion or condition. The 3 feature extraction techniques along with the SVM classifier thus classifies the dataset to the most accurate percentage.

Md. H. Kabir, et al. (2010) [22] implemented an LDP field descriptor feature for object detection. LDP code calculating sting answer values in several directions and encoding the local image property using this. The LDP descriptor's discriminative power comes from the incorporation of local edge response into one binary sequence, giving it robustness and freedom from being sensitive to changes in non-monotone lighting and noise. Experimental results showed that the LDP descriptor on database of the Brodatz textures

had a higher classification accuracy which LDP descriptor uses the FERET database to give better accuracy of recognition in face recognition.

N. M. Ali, *et al.* (2012) [11] researched item detection using local binary patterns and reported that similar object detection should benefit from separate LBP values as well as misleading the system to work out the item detected. Additionally, the first LBP can only reach limited local knowledge owing to its user serving a tiny area of small community.

S Krishnan, *et al.* (2016) [16] covers the effects of the simulation obtained in MATLAB 2010a on implementation of the program proposed. The findings were measured using 15 Glaucomatous pictures and 15 Normal pictures. With the “Polynomial” kernel function of the SVM classifier, 80% of the dataset was trained(24 images), while the rest of the percentage (6 photos), was tested. The framework uses the function extractor Histogram of Directed Gradients and categorizes the images using an SVM. The paper suggested that the algorithm which is mainly used for human identification may also be used in the medical field.

Dawei Nie, *et al.* (2011) [23] published the extraction and classification outcomes of its datasets (melanoma and nevus). The classification results ended up to be 80%. The better findings reported showed that the texture characteristics of tumors are key features and essential to use in the selection, examination and classification of tumor features.

S. J. Salasche, *et al.* (2000) [3] suggested his result in such a way that Actinic keratosis is normal in fair-skinned patients subjected to large levels of UV. While the likelihood of person AK turning into SCC is not strong, he indicated they are valuable indicators for sun exposure and risk evaluation of skin cancer. Combining treatments for treating AK is of growing concern, particularly when therapeutic choices increase-. The final option of medication, though, would be focused not just on effectiveness but also associated adverse effects, clinical results, quality, expense, enforcement, and patient preference.

Jiayue Cai, *et al.* (2019) [8] collected 143 lesions from melanoma and SK. Related approaches were used for the distinction of the dataset, and the findings indicated that the most accurate classification efficiency was obtained by the SVM, resulting in 86.31 per cent high precision and highest correlation between responsiveness and precision.

S. V. Shinde, *et al.* (2017) [24] whose paper can represent a Similar Carcinoma Detection Method Using Dermoscopy Pictures. The median filter is used for the pre-processing during this article. We use clustering of the K-means to achieve segmentation, then, the features were extracted. For classification the SVM classifier is used.

J. Stallkamp, et al. (2007) [25] have implemented a mobile facial recognition system that is extended to laptops utilizing a typical image processing webcam. The classifier of hair characteristics, centered on the specific regions was defined by skin colour. They were used to record images of the nose. LBP has been used for preprocessing facial regions to reduce effects on lighting. The testing scenario was done on sequential dataset of 42 from 14 subjects and resulted into an accuracy of 79 %.

III. METHODOLOGY

In this research we used images of AK(Actinic Keratosis),SK(Seborrheic Keratosis) and Nevus skin lesion as datasets. The dataset is split between learning and teaching sets (70 per- cent is used in research and the remainder is used in testing). Next comes extractions of the functionality. The methods used in this paper include LBP, HOG, and LDP. These methods are merely tools or algorithms for extraction purposes of features only so we need an SVM classifier to identify extracted features.

A. LBP (Local Binary Pattern)

This method is always the most important of the steps in performing image recognition. In 1996,D. Harwood *et al*[17] made the LBP methods popular. It illustrates the shape and texture of an image very effectively.

LBP is an optimal texture operator that marks image pixels by thresholding each pixel neighborhood, and determines binary results. The LBP works between each adjacent pixel by setting a centre-pixel threshold. If the adjacent pixel value is equal to or higher than the centre-pixel value, denote it with 1 otherwise 0.

As an example, let us consider the original LBP descriptor that operates on a settled 3 by 3 neighborhoods of pixels:

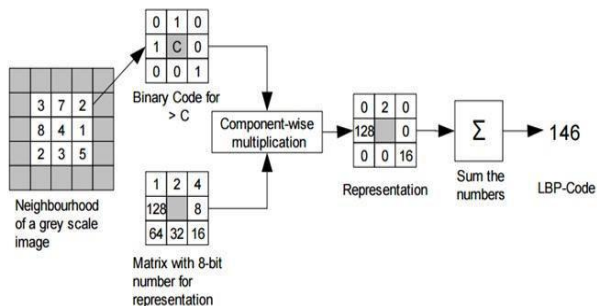


Fig.4: The construction of LBP by considering 8 neighborhood pixels that surround the center pixel and applying a threshold to each pixel, resultingly finding out the LBP code for each pixel values

B. HOG (Histogram Of Oriented Gradients)

HOG algorithm is the so-called major, simple and efficient method of extracting features. Compared to SIFT and SURF forms, it is faster and more efficient by its simplicity. Image shape and appearance can be represented with HOG. This splits the picture into small cells used in this research such as 4x4, and calculates the edge directions. To maximize precision the histograms can be normalized[18]. The HOG descriptor centers on an object's form, or design. We'll only decide whether or not the pixel is an edge. HOG provides edge directions which are calculated in localized sections. It ensures the whole picture is split down into smaller parts, and the gradients and direction for each region are determined. The HOG will eventually produce a separate histogram for every single one of these areas. The histograms are created with pixel value gradients and orientations. Our emphasis in this paper is therefore on how such functions are determined in Digital Image Processing's MATLAB tool. The process of calculating HOG in depth phase by stage is:

C. Preprocess the Data

Pre-process the image, and its overall ratio to 1:2. Size of image must be 64x128. Because, to extract the features, we will divide the image into 8 * 8 and 16 * 16 sections. With

the size specified (64x 128), all our calculations will be quite simple.

D. Calculating Gradients (direction x and y)

Each and every tiny patches are picked from images, and its gradients are determined on that. For this patch we must receive the pixel values. Let's say for the specified patch we produce the pixel matrix below (the matrix presented here is merely a case in point).

121	10	78	96	125
48	152	68	125	111
145	78	85	89	65
154	214	56	200	66
214	87	45	102	45

Fig5:A Matrix of pixels which is a patch from an image, as example.

To evaluate the change in the x-axis, the left-hand value must be subtracted from the right-hand pixel value. Likewise, to measure the gradient in a y-direction, the pixel value below must be subtracted from the pixel value above the chosen pixel. For all pixels within the image the same cycle is repeated.

E. Calculate the Magnitude and Orientation

Now we will specify the magnitude and direction of every value of pixel using the gradients we've determined in the last step.

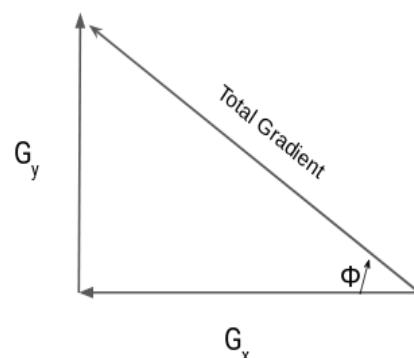


Fig 6: Pythagoras theorem representation to calculate gradient.

The gradients here are baseline and perpendicular. Thus to measure the magnitude of the overall gradient :

$$\text{Total Gradient Magnitude} = \sqrt{[(G_x)^2 + (G_y)^2]} \quad (1)$$

the value of the angle is:

$$\Phi = \text{atan}(G_y / G_x) \quad (2)$$

F. Calculate Histogram of Gradients

For the entire image, the histograms produced in the HOG function descriptor aren't developed. The picture is instead fragmented to 8x8 cells, and for each cell the histogram of directed gradients is determined. Through this, for the smaller patches we get the features (or histogram), that represent the entire picture in effect. This value will definitely be modified here from 8x8 to 16x16 or 32x32. The greatest gain will be in the direction of the bin with respect to the position of the pixels.

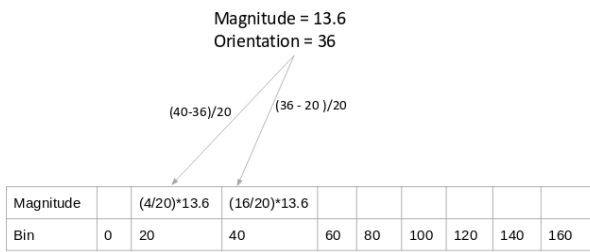


Fig7: Histogram calculation method

a) Normalization of gradients in 16x16 cell (36x1)

In mathematical terminology, for a given vector to be solved into a normalized one, the following steps are performed :

$$V = [a_1, a_2, a_3, \dots, a_{36}] \quad (3)$$

Calculating the squares' total root:

$$k = \sqrt{a_1^2 + a_2^2 + a_3^2 + \dots + a_{36}^2} \quad (4)$$

Dividing all the vector values with this value k:

$$\text{Normalised Vector} = \left[\frac{a_1}{k}, \frac{a_2}{k}, \frac{a_3}{k}, \dots, \frac{a_{36}}{k} \right] \quad (5)$$

b) Features for the complete image

We have 16x16 blocks of 105 (7x15). Each of these 105 blocks has as features a vector of 36x1. The cumulative features for each picture will then be 105x 36x1= 3780 features. For HOG parameters, in order to describe the right parameter configuration further training and testing procedures have to be done using the classifier.

c) LDP (Local Directional Patterns)

Modern analysts and researchers use a pixel-specific shift in gradient magnitude to represent local texture [19] and [20] during a given direction. Such strategies measure the gradient magnitude of adjacent pixels along the selected path rather than measuring and encoding the neighboring strength value as insubstantial LBP. It takes into account the magnitude of single-directional edges only. Considering this conclusion, we implemented the LDP (Local Directional Pattern) image feature, which calculates in several directions the string address values; it then uses these for encoding image textures.

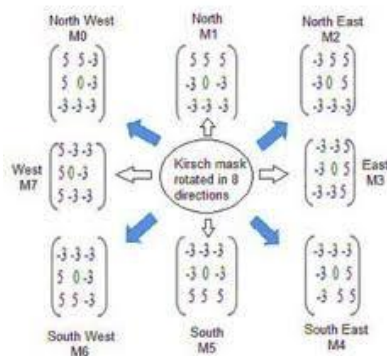


Fig.8: All 8 directions for the Kirsch edge response masks.

This is an 8-bit code. It is allocated to individual pixel that constitutes the image. This pattern is computed in several ways. One of the representative edge detectors, Kirsch masks M_i , and measures the mask values, where i ranges from 0 to 7, based on their location in eight different orientations, provided a central pixel inside the image.

Those masks are used in the fig. 8. In some specific directions a corner or edge intervention indicates higher values of reaction. So, we're interested in understanding the k 's most influential paths for the LDP. Here b_i is set to the maximum response of directional bit k . The remaining 8- k bits are assigned as 0. Eventually, the code springs to (6). Fig. 9 Shows the response mask and the positions of the LDP bit, and Fig. 10 does have undesirable LDP code of $k=3$ [14].

$$LDP_k = \sum_{i=0}^7 b_i (m_i - m_k) \times 2^i$$

$$b_i(a) = \begin{cases} 1 & a \geq 0 \\ 0 & a < 0 \end{cases} \quad (6)$$

where, m_k is the k -th most relevant directional response.

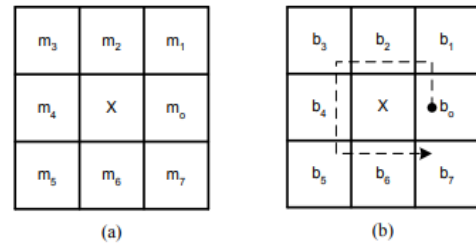


Fig. 9: (a) 8-directional edge response positions. (b) Matrix(in terms of 0's and 1's).

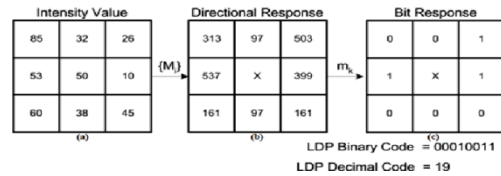


Fig.10: Code when k is assigned the value 3.

d) Classifier

Dataset recognition applies to a method in computer vision that can classify items according to their characteristics. This classification helps to categorize data sets or images as "Actinic keratosis", "Seborrheic keratosis" or "Nevus (non-cancerous moles)". The image sets are used both for training and for testing.

e) SVM

SVM was conceived, designed and built by Vapnik *et al.* (1998) [21]. Multiclass SVM is selected as the classifier for the detection of skin keratosis lesions. Here, the classification is based on assigning the labels each during the training process for AK, SK and nevus skin lesions. The kernel feature helps convert the knowledge into another higher dimension which has a simple hyperplane. A large part of the kernel functions used are RBF, linear, and polynomial.

Linear Kernel

This kernel is used when the functions can be isolated linearly. It is mostly used when a given dataset contains a huge number of features. One of the main advantages of this kernel is that when the SVM preparation is completed it is faster than any other kernel.

$$k(x, y) = x^T y + c \quad (7)$$

Polynomial kernel

The polynomial kernel is well adapted for problems when the entire trained data is normalized.

$$k(x,y)=\alpha x^Dy+a \quad (8)$$

Where 'a' is the constant term, D is the polynomial degree and adjustable parameters are the slope α .

RBF

RBF is otherwise recognized as the Gaussian kernel, which is a radial basis function in form. The RBF kernel is defined as

$$K_{RBF}(x,x')=\exp[-d||x,x'||^2] \quad (9)$$

Where 'd' is a parameter that sets the "spread" of the kernel.

Evaluation Metrics

Every system's performance depends primarily on how precisely the features are extricated from the input file. For classification a misunderstanding matrix is used to summarize the performance.

$$\text{Accuracy } A = (x/y) * 100 \quad (10)$$

Here, 'x' = total no. of correct classifications; 'y' = no. of samples.

IV. EXPERIMENTAL ANALYSIS AND RESULTS

A. Dataset and Implementation

In this research we analyze and categorize melanoma from non-melanoma skin lesions. Datasets were obtained from the website 'www.kaggle.com,' which included 1,200 images each of Actinic Keratosis, Seborrheic Keratosis and Nevus skin lesions. All of the above data sets are critical to prepare, check and advance to the methods of classifying the 2 skin disease datasets and nevus(moles).

The computational algorithms have been designed and developed in the program MATLAB version 2015b. The entire dataset was separated into the training and testing parts. Approximately, 70 % is used for preparation, and the remainder is used in practice-to illustrate and begin evaluating the efficiency of the algorithms considered. To order to extract the attributes, the LBP, LDP and HOG methods are applied to the images and, as a result, three SVM kernels are added one after another to determine the predictive precision. These methods run with three of the SVM classifier kernel features, i.e. RBF, polynomial, and linear, respectively. The accuracy varies slightly, depending on the different functions used for the kernel. The corresponding accuracy of both methods is shown in the table in the segment that follows the Work Flow Diagram.



Fig.11:Work Flow Diagram

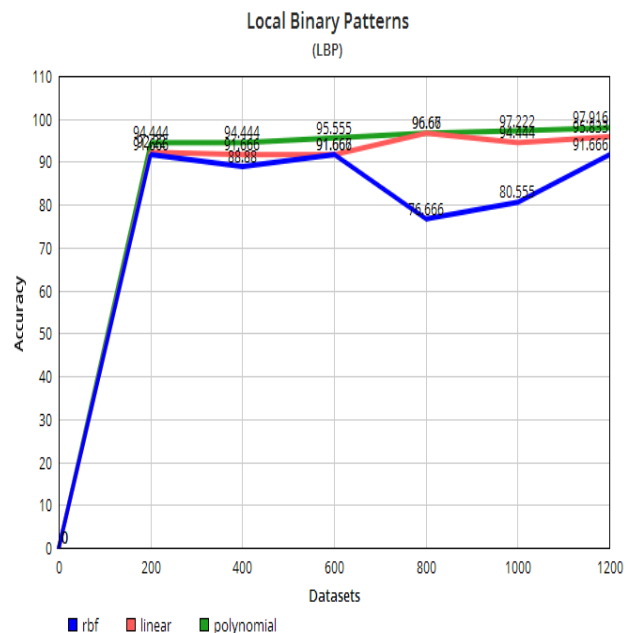
V. RESULT

The first table shows results achieved by applying the three functions of the SVM kernel using the datasets on the two LBP and LDP methods:

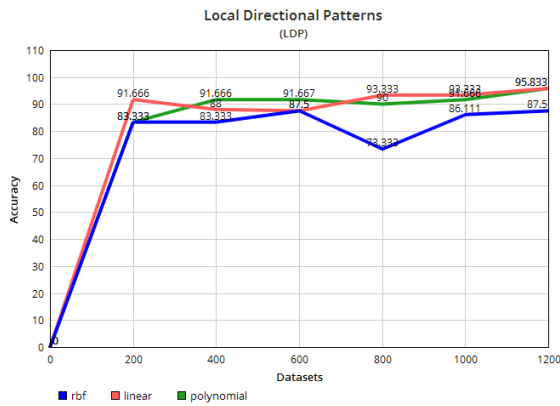
Table I: Illustrates the performance of each kernel function's highest values for different number of datasets using LBP, LDP and HOG processes and the SVM classifier.

Dataset	Method	Accuracy by Kernel Functions (in %)		
		RBF	Polynomial	Linear
AK,SK and Nevus Skin Images	LBP	91.667	97.916	96.667
	LDP	87.5	95.83	95.833
	HOG	80	95.83	91.667

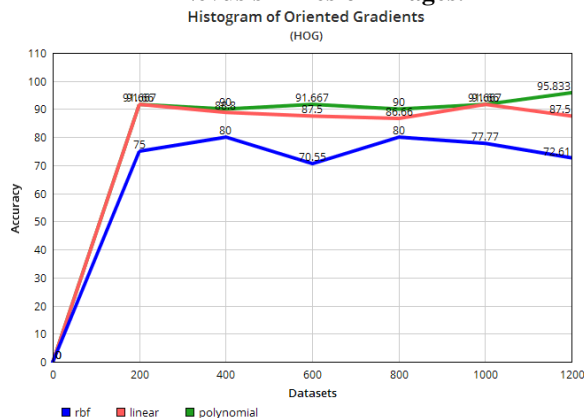
The respective graphs of the three methods LBP, LDP and HOG are plotted against the numbers of increasing data sets for their detection or classification, where their accuracies are:



Graph I: Illustrates the LBP method and that the Polynomial SVM function shows better accuracy in classification of Actinic Keratosis, Seborrheic Keratosis and Nevus skin lesion images.



Graph II: Illustrates the LDP process and demonstrates better accuracy of the Linear SVM feature when classifying Actinic Keratosis, Seborrheic Keratosis and Nevus skin lesion images.



Graph III: Illustrates the HOG method and demonstrates better accuracy of the Polynomial SVM feature when classifying Actinic Keratosis, Seborrheic Keratosis and Nevus skin lesion images.

Both, the LDP and HOG methods along with SVM classifier primarily classifies the dataset with accuracies in the range 70-96 %. The LBP method, individually, scales its images or dataset in the range 80-97 %. This indicates that together with SVM and its "Polynomial" kernel function, the LBP (Local Binary Pattern) method gives a better accuracy along datasets to classify Actinic Keratosis, Seborrheic Keratosis and Nevus skin lesions. Together with SVM and its "Linear" kernel function, the HOG (Histogram of Oriented Gradients) method gives the next stronger precision numbers according to the charts. The LDP (Local Directional Pattern) gives almost the least precision of all the three methods.

VI. CONCLUSION AND FUTURE WORKS

The collection consisted of 1200 Actinic Keratosis, 1200 Seborrheic Keratosis and 1200 Nevus skin lesion photographs. The LBP (Local Binary Pattern) approach along with SVM and its "Polynomial" kernel function gives better precision over datasets to identify or discern each of the 3 types of skin lesion images when based on the three attribute extraction methods and when categorized using the SVM classifier. The accuracy of the above-mentioned method LBP-SVM(Polynomial) ranges from 94-98 %. Considering the graph values, the HOG (Histogram of Oriented Gradients), along with SVM and its "Polynomial" kernel function gives the next better precision numbers in the 90-96 % range. According to the charts, the LDP (Local

Directional Pattern) method along with SVM and its "Linear" kernel function gives the next better precision numbers in the 87-96% range. Thus, in comparison with SVM, this research recommends the LBP-SVM(Polynomial) method for classifying Actinic Keratosis, Seborrheic Keratosis and Nevus skin lesion images so that the Seborrheic skin condition could be treated and the main condition called Actinic Keratosis lesion images could be detected and both be separated from Nevus. Thus, the Actinic Keratosis can be treated immediately by the doctors at the early stages of the disease, or as soon as possible, before it could turn into the deadly squamous cell carcinoma skin cancer. Nevus skin lesions, on being separated or classified from the 2 other datasets could also be treated, as it might, very rarely, turn into melanoma or other skin cancers. In the possible future, there is even more advanced LBP which could be researched to fulfill the image detection task. Given that this method or algorithm is found finer than the other two well-known feature extraction algorithms, it can evolve (algorithm wise) and generalize more of object-detections, even in the medical field thus saving lives in the result of their further medical processes.

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