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Darier Disease-A Genetic Disorder Detection in the Light of Computer Vision

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ABSTRACT

This paper deals with the detection of a genetic disorder called Darier disease manifested in dermal changes. The clinical diagnosis of the said disease motivates its recognition in the light of computer vision which incorporates three methodologies based on 1) gray level co-occurrence matrix (GLCM), 2) local binary pattern (LBP) and 3) wavelet energy feature for skin texture feature extraction. The feed forward neural network (FNN) is implemented for Darier disease detection. All the methodologies are thoroughly compared to find the most suitable one as skin texture screening tool. The GLCM, LBP and wavelet based methodologies attain Darier disease detection accuracy of about 82%, 82% and 89% respectively. The other aspect of this work is that GLCM based methodology addresses the presence and location of several typical skin texture abnormalities by the statistical plots drawn against user defined offsets (spatial relationship between two pixels).

Keywords: Computer vision, Offset, Training, Testing, Validation.

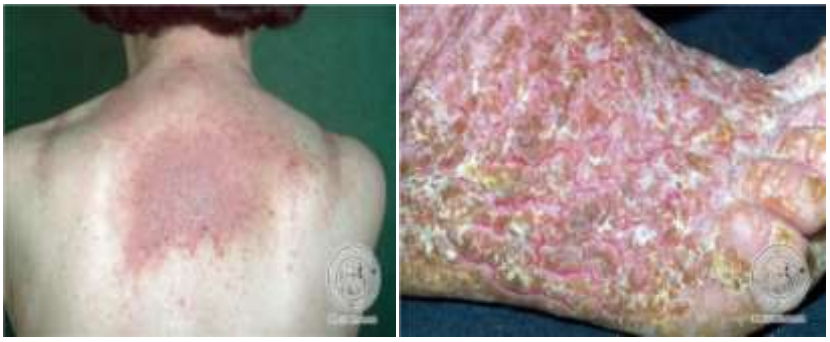
1. INTRODUCTION

With the advent of computer-aided diagnosis, there is a rapid development of dermatology. It helps to remove subjectivity and unreliability from conventional diagnosis. The dermatologists can develop a second opinion from the computerized skin screening technology.

A vast literature [1] is available on computer supported skin cancer investigation and characterization. Garnavi *et al.* [2] address the detection of malignant melanoma with the help of wavelet based textural analysis. The erythemato-squamous diseases like psoriasis, pityriasis rubra pilaris, seboreic dermatitis, pityriasis rosea, lichen planus and chronic dermatitis share common clinical features with little differences. So they are very difficult to differentiate. Übeli and Doğdu propose the automated detection of the above diseases by *k* means clustering. The identification of leprosy, tinea versicolor and vitiligo which closely resemble each other in lesion pattern and color is demonstrated by Das *et al.*[3].

But the detection of Darier disease in the light of computer vision is hardly addressed in the scientific literature. Darier disease is an unusual genetic disorder which is predominantly expressed by dermal changes [4]. The genetic disorder is inherited in autosomal dominant mode. This means the abnormal gene transmitted from a single parent to a child can cause this dermal condition. The disease inheriting probability of a child born out of two children of one affected parent is 50%. It is a non-contagious and chronic disease found in both male and female during the adolescence period. The skin becomes scaly and brownish. Innumerous greasy papules look like rough sandpaper. They appear on different parts of the human body like eye brows, forehead, sides of nose, neck, central chest, under breast, upper back, in between buttocks, groin, nail, foot etc. The papules often fuse together to form large smelly warts on the skin surface as shown in Figure 1[5]. The cells of a normal skin stick together with the help of molecular complexes called desmosomes. But here, due to the presence of the unusual gene *ATP2A2* traced on chromosome 12q23-24.1, the desmosomes fail to adhere the skin cells for lack of sufficient calcium [4]. Some patients carry the diseases but do not show any noticeable symptom. While others have widespread lesions often flared by sunlight. The disease becomes intolerable when it is exacerbated by either bacterial or viral infection. As a result the patient suffers a lot of pain and agony. Keeping in view of the change in dermal surface morphology and clinical approval of appearance based diagnosis [4], [6], this particular disease is investigated in the perspective of computer vision.

In this paper, we propose the detection of Darier skin disease by 1) GLCM), 2) LBP, and 3) wavelet based approaches. Earlier, all the three approaches are implemented individually in applications like [3] and [7]. But proposed methodology brings together three time tested data extracting tools on a common skin disease detection platform to investigate the individual tool's disease detection accuracy followed by overall comparison. Moreover, Mitra *et al.* [8]



(a) (b)

Figure 1. Image of Darier disease (a) upper back with mild infection (b) foot with severe infection [Source: Diepgen TL, Yihune G et al. Dermatology Online Atlas]

demonstrates the automated skin disease identification by considering only the average of directional GLCMS and the exact number of skin characterizing features remains ambiguous. But our GLCM approach not only computes the statistical features – contrast, correlation, energy, homogeneity along four directions $(\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ)$ as shown in Figure 2 a), but also incorporates 8 offsets along each direction to find distance wise average GLCM. This facilitates the dual sensitiveness of proposed GLCM along direction and distance. The other salient feature of this approach is that the typical textural information e.g., periodicity of any particular lesion can be intensely investigated by the statistical parameter versus offset plot. The second approach of LBP is computationally simple and invariant to changes in gray level and rotation of an image. It is already popular amongst several image processing applications like face recognition, facial expression identification. But it is limitedly used in medical applications [3]. So its versatility is experimented herewith. The third approach deploys four different wavelets called Daubechies (DB), Discrete Meyer (DM), Symlet (SY) and Biorthogonal (BO) for 3 level decomposition of skin disease images resulting in one approximation and three detail subbands at each level of decomposition. As the subband wise energy distribution at any given level of wavelet decomposition has the image discriminative property, so it is used here as a skin texture characterizing feature.

The rest of the paper is organized as follows. Section 2 deals with the proposed methodology. The experimental results are discussed in Section 3. The conclusion is drawn in Section 4.

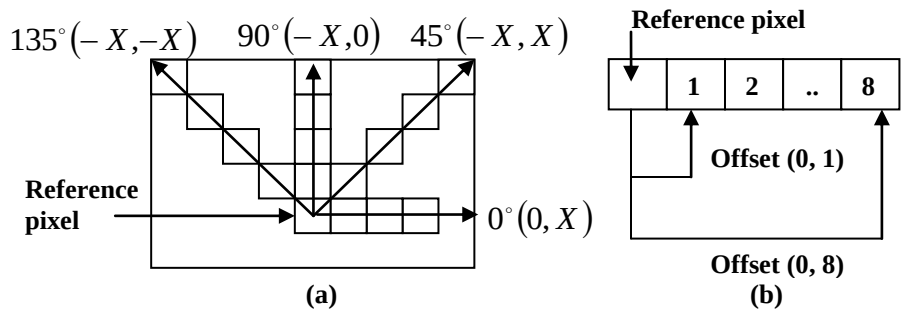


Figure 2. Defining offsets : (a) along four directions where X represents the distance [9], (b) horizontal offsets with distance X=1 and X=8 .

2. PROPOSED METHODOLOGY

In Figure 3, we present three discrete modules founded on -1) GLCM, 2) LBP and 3) wavelet by three parallel paths to detect Darier disease from skin texture images. Individual module mines textural features from the images of both the Darier and non-Darier (not Darier) skin diseases like Diabetic Gangrene, Scabeies, Ichthyasis Congenita and provide databases to the FNN for image detection. The methodology of individual module is discussed in the subsequent sub-sections.

A. Textural Analysis by GLCM Methodology

In this approach, matrix is first created from the input image. The statistical parameters are then evaluated from the matrix. The four offsets, i.e., horizontal $(\theta = 0^\circ)$offset, right diagonal$(\theta = 45^\circ)$offset, vertical $(\theta = 90^\circ)$offset, and left diagonal $(\theta = 135^\circ)$ offset are defined as shown in Figure 2 (a). As the skin texture varies along each direction, 8 distance offsets, i.e., [0,1] ……[0,8] as shown in Figure 2 (b) are incorporated to trace the horizontal variation of skin

texture. Using the 8 horizontal offsets, 8 GLCMs are found and the average horizontal GLCM is created. In a similar way the average GLCMs are found along four directions. Now, the direction wise statistical parameters are calculated from horizontal, right diagonal, left diagonal and vertical based GLCMs as illustrated in Table 1. Table 1 showcases the textural features of only five Darier disease images. Using the same technique textural features of non-Darier skin images are tabulated in Table 2. Tables 1 and 2 are used to create the input and target databases and provided to FNN for image detection.

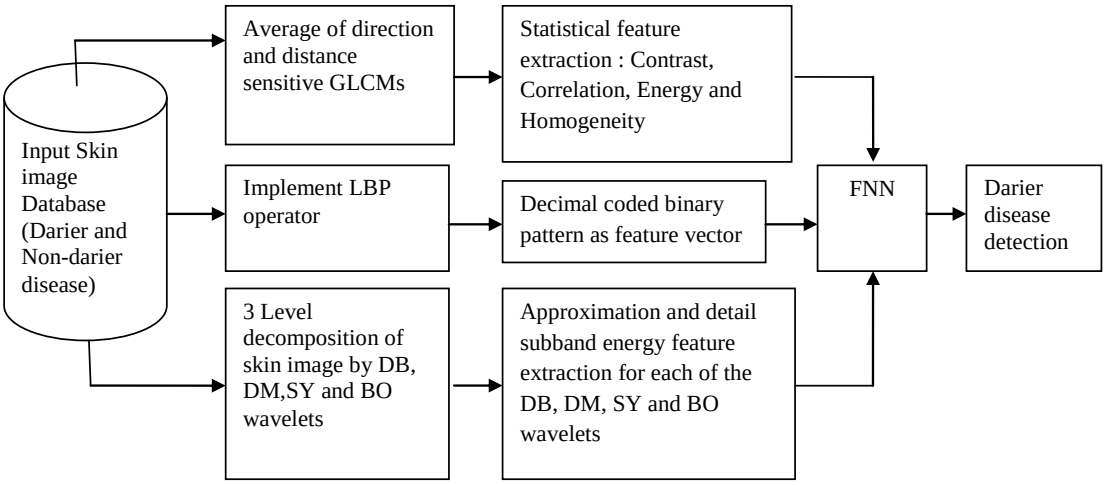


Figure 3. Schematic of proposed methodology where GLCM: Gray level co-occurrence matrix, LBP: local binary. DB: Daubechies, DM: Discrete Meyer, SY: Symlet, BO: Biorthogonal wavelets. FNN: Feedforward Neural Network

Table 1: The statistical features obtained from the average GLCM of Darier skin images. Deg: Degree

Im No.	Contrast				Correlation				Energy				Homogenity			
	0 Deg	45 Deg	90 Deg	135 Deg	0 Deg	45 Deg	90 Deg	135 Deg	0 Deg	45 Deg	90 Deg	135 Deg	0 Deg	45 Deg	90 Deg	135 Deg
1	1.51	2.19	1.69	2.53	0.83	0.74	0.80	0.70	0.05	0.05	0.05	0.04	0.76	0.69	0.74	0.69
2	0.44	0.85	0.66	0.63	0.95	0.91	0.93	0.93	0.08	0.06	0.07	0.07	0.85	0.75	0.82	0.84
3	0.92	1.57	1.31	1.47	0.89	0.82	0.85	0.83	0.05	0.04	0.05	0.04	0.76	0.69	0.70	0.69
4	2.90	4.02	1.66	3.84	0.66	0.52	0.81	0.54	0.03	0.03	0.05	0.03	0.58	0.54	0.72	0.54
5	1.70	2.19	0.87	2.30	0.80	0.73	0.90	0.73	0.05	0.04	0.06	0.04	0.71	0.65	0.79	0.65

B. Textural Analysis by LBP Methodology

LBP is a mathematical operator which is commonly used for texture classification. The LBP of a particular pixel is calculated by considering only the sign of the difference of gray levels of that pixel with the defined surrounding pixels. The primary attribute of LBP, i.e., gray level invariance can be mathematically derived from [10] as below. Let $I(x,y)$ be a two dimensional monochrome image where g_c is the gray level of a random pixel (x,y) given by $g_c = I(x,y)$. Similarly g_p be the gray level of a sampling point in a circular neighborhood with P samples and radius R around the point (x,y). So it can be written as $g_p = I(x_p, y_p)$ *where* $p = 0,...P-1$; $x_p = x + R\cos(2\pi p/P)$; $y_p = y - R\sin(2\pi p/P)$. It is known that local texture of image $I(x,y)$ depends on the joint distribution of the gray values of $P+1$ pixels where $P > 0$. That is, $T = t(g_c, g_0, g_1, g_2, ..g_{P-1})$. Now the central pixel which in this case is the arbitrary pixel can be subtracted from each member of neighborhood without causing any information loss. $T = t(g_c, g_0 - g_c, g_1 - g_c, g_2 - g_c, ..., g_{P-1} - g_c)$. As g_c is independent of $g_p - g_c$, the above equation can be further simplified as $T \approx t(g_c)t(g_0 - g_c, g_1 - g_c, g_2 - g_c, ...g_{P-1} - g_c)$ where $t(g_c)$ denotes intensity

distribution of $I(x,y)$ and carries no useful information in the context of textural pattern. But the second factor of the above expression can be exploited to represent the local texture pattern by considering the signs as mentioned below. $t(s(g_0-g_c), s(g_1-g_c), s(g_2-g_c), s(g_{P-1}-g_c))$ such that $s(z)=1$ for $z\geq 1$, $s(z)=0$ for $z<0$. In general LBP is obtained from the joint distribution mentioned by the earlier equation. The basic LBP is found by adding the thresholded differences being multiplied by powers of 2 as given below.

$$LBP_{P,R}(x_c,y_c)=\sum_{P=0}^{P-1}s(g_p-g_c)2^P \qquad (1)$$

The LBP is made rotational invariant by clockwise rotating the set of neighbor pixels. The number of rotations varies till the maximum number of most significant bits in the binary pattern is zero. Mathematically, $LBP_{P,R}^{ri}=\min\{ROR(LBP_{P,R},i)\}$ for $i=0,1,2,3,...P-1$. Here, $ROR(x,i)$ performs the circular bit-wise right shift operation on the P bit number for x,i times. The physical significance of equation (1) is that it represents a *P* bit binary number and provides 2^P discrete values of LBP code. In our work we have found the LBP of both the Darier and non-Darier skin images and store the information in histograms. Since we work with ordinary LBP, it has 2^P or $2^8=256$ bins in the histogram. Later the histograms of the two types of skin images are used to create the input and target databases to be supplied to FNN for image detection.

C. Texture Analysis by Wavelet Methodology

Each of the two dimensional discrete wavelet transforms (DB, DM,SY, BO) decomposes the skin image into one coarse approximate subband and three detail subbands with the help of low pass and high pass filters respectively. The approximation subband so obtained is decomposed twice to result in one approximation and three detail subbands at each level of decomposition. The four subbands - approximation suband, detail horizontal subband, detail vertival subband and detail diagonal subband generated after 1st level of decomposition are represented by the coefficient matrices given by A _1, D_H_1, D_V_1 and D_D_1. As each of the matrices contains too many coefficients, individual matrix is replaced by the average of the coefficients which can be expressed from [7] as

$$D\_H\_1=\frac{1}{p\times q}\sum_{x=\{p\}}\sum_{y=\{q\}}|D\_H\_1(x,y)| \qquad (2)$$

$$D\_V\_1=\frac{1}{p\times q}\sum_{x=\{p\}}\sum_{y=\{q\}}|D\_V\_1(x,y)| \qquad (3)$$

$$D\_D\_1=\frac{1}{p\times q}\sum_{x=\{p\}}\sum_{y=\{q\}}|D\_D\_1(x,y)| \qquad (4)$$

The coefficients of A_1 are not averaged since it undergoes further decomposition. The squaring based energy of the three detail subbands (matrices) can be obtained from equations (2), (3) and (4) as

$$E\_D\_H\_1=\frac{1}{p^2\times q^2}\sum_{x=\{p\}}\sum_{y=\{q\}}(D\_H\_1(x,y))^2 \qquad (5)$$

$$E\_D\_V\_1=\frac{1}{p^2\times q^2}\sum_{x=\{p\}}\sum_{y=\{q\}}(D\_V\_1(x,y))^2 \qquad (6)$$

$$E\_D\_D\_1=\frac{1}{p^2\times q^2}\sum_{x=\{p\}}\sum_{y=\{q\}}(D\_D\_1(x,y))^2 \qquad (7)$$

Hence, the total energy of the three detail subbands related to 1st level decomposition can be expressed as ED1 where

$$ED1=E\_D\_H\_1+E\_D\_V\_1+E\_D\_D\_1 \qquad (8)$$

Similarly ED2 and ED3 can be computed for the 2nd and 3rd decomposition levels. The approximation subband energy EA of the 3rd (last) decomposition level is computed on similar formulation background of equations 2 and 5. Like GLCM or LBP based methodologies, input and target databases are also created to provide the FNN for image classification.

D. Darier Skin Image Detection by Feedforward neural Network

The FNN is formulated on the basis of conjugate gradient back propagation algorithm. It has three layers namely the input layer, the hidden layer and the output layer. Here the hidden layer has 20 neurons. When the texture features of all the skin images are computed by each individual module, two databases are created. The input database comprises of the characteristic features of all the input images. While the target database categories Darier and non-Darier skin images of input database as "1" and "0" in the corresponding location. That means after database creation, every module provides one input and one target database to FNN. The FFN network is trained with 70% of the input samples. The training is validated with 15% of the remaining fresh samples. And the other remaining 15% samples are used for

testing. So FNN detects the Darier diseases separately for three modules and the results so obtained are discussed in the following section.

3. EXPERIMENMTAL RESULTS AND DISCUSSION

The complete experiment is performed in Matlab 7.14.0.739 (R2012a). Seventy (Darier: thirty five and non-Darier: thirty five) skin disease images are taken from [5]. The FNN receives one input and one target database from each of the three parallel modules shown in Figure 3. It is independently trained, validated and tested with 3 different sets of input and target databases. The results of the Darier disease detection by FNN in terms of the performance indexing parameters (PIP) like percentage of correct training, validation, testing and classification of the input skin texture images are pictorially represented in Figure 4. It is found from Figure 4, that the wavelet based approach of Darier desease detection is better than both GLCM and LBP based approaches in terms of all the PIP. So, the PIP of the FNN for only wavelet based approach is presented in Figure 5 (a). Figure 5(b) represents the performance plot of FFN for the same approach. The mean square error versus number of iterations of FNN is displayed for all PIP. The percentage of correctly testing the the samples of GLCM and LBP approach by FNN is same and about 73%. The above two methods also provide the same Darier disease detection accuracy of about 82%. The difference of the two approaches lies in the

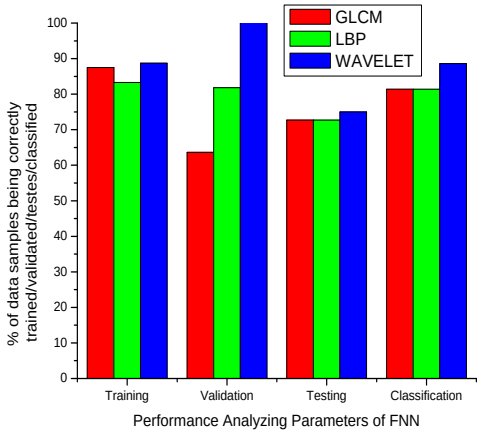
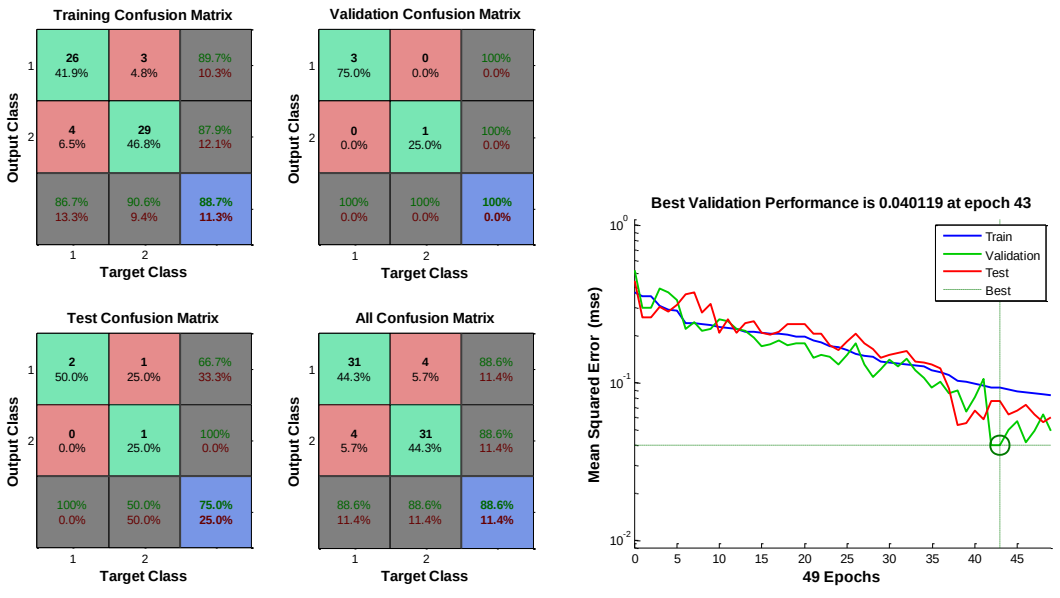


Figure 4. Comparison of GLCM, LBP and Wavelet based approaches in terms of the performance analyzing parameters of FNN.



(a) **(b)**

Figure 5. Performance analysis of Wavelet Based Approach (a) Confusion matrices: Training, Validation, All confusion and Testing matrices (from top clockwise) obtained from the FNN. (b) The mean square error versus number of iterations (epochs) as obtained from the performance plot of the neural network.

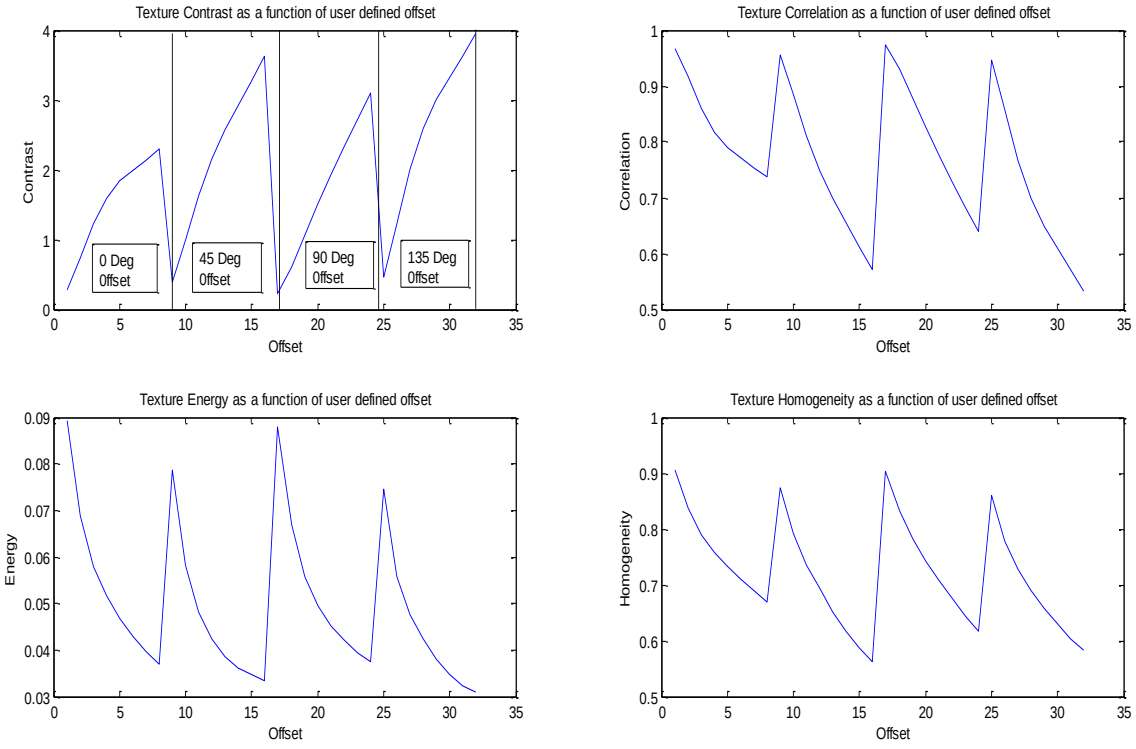


Figure 6. Plot of skin textural contrast, correlation, energy and homogeneity variation as a function of offset. Deg: Degree. The angle wise offset partition true for all the plots is shown in the first plot.

correct training and validation by the FNN. Though the correct network training $(\approx 88\%)$ by GLCM scheme is better than LBP approach $(\approx 84\%)$, LBP scheme supersede the former in terms of correct network validation. But the other notable advantage of GLCM approach is its offset wise intense investigation of the statistical parameters as shown in Figure 6. As the skin texture image contains a wide variety of shapes and sizes located along the horizontal, vertical and diagonal directions, this particular aspect is strongly portrayed in terms of the variation of the contrast, correlation, energy and homogeneity with the variation in offsets. As the offsets are multidirectional i.e., along $\theta = 0^{\circ}, 45^{\circ}, 90^{\circ}\ and\ 135^{\circ}$ as shown in the Figure 6 (top left), the rise or decline trend of the statistical parameters is thoroughly investigated. Moreover, confining offset to any particular direction, say horizontal; the vertical abnormalities can be located in the skin texture can be detected.

4. CONCLUSION

This investigation illustrates the detection of Darier disease by three different methodologies. This detection is probably the first time in the history of bioinformatics where a genetic disorder is identified by dermal imaging technique. The empirical data reveals that wavelet based approach is better than GLCM and LBP methodologies. Though LBP and GLCM methodologies achieve exactly the same correct rate of testing and classification; but considering the correct of training and validation, LBP methodology is the better choice. At this juncture, what deserves mentioning is the offset based statistical plots by GLCM methodology which provides typical skin textural information along different directions of an image. In future advanced wavelet like curvelet and contourlet may be implemented to test with the diseased skin image detection accuracy.

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