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SKIN CANCER LESION CLASSIFICATION USING LBP BASED HYBRID CLASSIFIER

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Abstract :Skin cancer is a most dangerous type of cancer found in humans. It is found in various types such as melanoma, basal cell carcinoma and squamous cell carcinoma. Among others, Melanoma is the most serious and dangerous cancer which leads from a simple skin mark to a tumour. Early detection of the type of skin cancer can helpsin better cure. In this paper, a new method is proposed for the detection of type of skin cancer. The proposed method integrates the features of DRLBP (Dominant rotated local binary pattern) and MRELBP (median robust extended local binary pattern) methods for feature extraction of the skin cancer lesions. The support vector machine (SVM) classifier is then used to classify the images based on the calculated features. To evaluate the performance of the proposed method, skin cancer images containing 367 lesions are used from ISICstandard dataset from the results, it is analysed that the proposed method can extracts microstructure and macrostructure texture information. Furthermore, it is robust to the rotation variation.It is also observed that the proposed method gives better results than the other state of the art local binary pattern based feature extraction methods.

Keywords: skin cancer, texture recognition, Local binary pattern, texture classification.

1. INTRODUCTION

Skin acts as an upper layer of defense against the external pollution, bacteria and germs. It is very sensitive and sensory part of the body. Melanoma is a type of skin cancer which is not common and it could be dangerous if it is not cured in time. It is lethal as compared to basal carcinoma and squamous cell carcinomacancer. However, Melanoma is curable disease but it is possible only in the initial stage. It can be identified by unusual growth of skin mark, colour of the skin lesion and shape of the boundary. Some thin melanoma lesion which are in few millimetre in diameter, cannot be detected by “naked eye”. The only possibility to diagnose them is by using computerised detection.
However, the death rate from skin cancer continues to increase yearly [1].The doctors and researcher have diagnosed about 170,000 new skin disease cases every year. Most approaches used to detect the Melanoma skin cancer emphasis on recognition of changing lesion colour, shape and other features. ABCDE (Asymmetry, Border, Color, Diameter and evolution) criteria commonly used for the diagnosis of early stage melanoma skin cancer [5] made this task easy for detection of skin lesion type [3] but there are some limitation arise in this criterion related to diameter of the lesion or border detection [4]. One of the most familiar method which is widely used all over the world is detection and classification of diseases in the input images.
Texture classification is the most advanced technology now a days. Byusing this technology, initial stage of skin cancer can be detected and identified. In image processing, digital image is processed and meaningful information can be extracted. The digital image serve as input and output can be a set ofparameters values related to the input image. In modern science and technology, image processing is able to perform operation on digital images, in order to get useful information to enhance the quality of the image and to understand the particular texture of the image. Many methods use texture and color data in image to find the lesion contour.
Texture extraction and classification is an important area in image processing, it works in many fields like face recognition, image segmentation, image classificationetc.In this work we have proposed a method which is applied on skin cancer images to eliminate the factor such as illumination, rotation variance. In the texture classification application, rotation variation can create immense problem due to the change in angle which occurs due to camera rotation or self-rotation. Rotation is divided into three categories: (i) Global image rotation: in this image is rotated with respect to values that computed at holistic level before extraction of features. (ii) Discard local orientation: in this local features are extracted by discarding information of local orientation. (iii) Local path rotation, in this local features are extracted by local dominant direction.
The texture descriptor proposed in this paper is based on Local binary pattern [6].Local binary pattern has high discrimitive power, invariance to gray scale variation and gives good performance. In spite of these merits, it has some limitation like (i) Descriptor is not invariant to rotation changes, (ii) The microstructure and macrostructure captured by LBP is limited and (iii) As the number of neighbours increases the computational complexity also increases.

2. RELATED WORK

In feature extraction, achieving rotation invariance is most challenging task. LBP is one of the methods used for extraction of features, but it is rotation variant and to achieve the rotation invariance different modification has been proposed in basic LBP methods. Ojalaet.al [7] proposed multiresolution gray scale and rotation invariant texture classification based on local binary pattern, it can efficiently detect the uniform patterns for any quantization of angular space and for spatial resolution but the information about local orientation is discarded. Adel wafiane et al [8] proposed a new approach to overcome the challenging problem of texture classification and recognition of image under illumination variation. Proposed a texture descriptor named Adaptive median binary pattern which is extended from Median binary pattern for enhancement of texture feature collection. This scheme use an effective mechanism for non-parametric learning of spatially varying image texture statistics. Priyadarshini. D et.al [9] proposed work on Melanoma which is a lethal skin cancer, it causes from the pigment containing melanocytes. This skin cancer can be detect by using linear binary pattern which is an efficiently used for texture analysis. It has a powerful feature of texture feature extraction. The SVM classifier used for classification of data. R.janaki et.al [10] proposed work on the detection of melanoma from the dermoscopic images, and segmented the image and then classified it. Result analysis and compare with different parameters like accuracy, error and for the classification of data, fuzzy classifier is used. Md.abdur Rahim et.al [11] proposed work on face recognition using local binary pattern, focus on human being facial information and use algorithms for detection and recognition. The face area divided into small regions from which local binary pattern (LBP) and then histogram generated and concatenated into a single feature vector. This measure similarities between images. Number of extensions of local binary pattern using for getting the best result and to achieve high discrimitive power. Chandraja.D et.al [12] proposed work on local binary pattern and describe the extension of local binary pattern.it surveyed and implement. The operator work on texture as well as face recognition. Lei Yang et.al [13] explained the face detection and tracking as well as sensitive image, in paper, RGB, Yeber, HSV color spaces are used to skin detection. It take advantage of gray statistics to extract textures features and implement skin detection with HSV color space for improvement in result. Li Liu et.al [14] proposed work on local binary pattern (LBP), it is very sensitive to image noise and unable to capture the macrostructure information. In paper, they introduce a descriptor for texture classification, Median Robust Extended LBP (MRELBP) which is different from other existing methods or conventional descriptor. In this, multiscale LBP type descriptor is computed and compare median over the sampling scheme and which can able to capture both macrostructure and microstructure information. Rakesh Mehta et.al[15]proposed approach not only hold the complete structure information extract by LBP, but also collect the gratuitous information by utilizing the magnitude data to achieve more descriptive power.

3. TEXTURE CLASSIFICATION USING LBP BASED HYBRID DESCRIPTOR

In this part, we describe the proposed technique. Firstly, we discuss about the roots of this approach and give brief information about it, and then we discuss about the elimination of rotation variation and extraction useful information.

Background

The LBP operator is proposed by Ojala with et.al [1]. It calculates values taking difference of central pixel with respect to its neighbours, consider only the sign to convert in the binary form. It is defined as

$$LBP_{R,P} = \sum_{p=0}^{P-1} s\left(g_p - g_c\right).2^p, \quad s\left(g_p - g_c\right) = \begin{cases} 1 & g_p \geq g_c \\ 0 & g_p < g_c \end{cases} \tag{1}$$

Where, R is radius of circular neighbourhoodregion, P represents the number of the neighbours. p is the index of the neighbours, $g_c$and $g_p$are the gray level values of central pixel and neighbour of central pixel respectively. A local binary pattern is called uniform, if its binary code form contains at least two transition from 0 to 1 or vice versa. By using equation (1), we can calculate LBP.

The LBP operator computes the value which is the difference of central pixels with its neighbour pixel and assigns the signs to these differences with different and unique weights. For example, for the neighbour pixel g_0 signs weight is 1 and next pixel g_1 is 2 and so on. If the image faces the problem of rotation (whether it is camera rotation or self-rotation), the arrangement of pixel around the centre pixel undergoes a change. By this rotation change, the order of the fixed weighted values changes and hence the LBP results also changes. In this way, LBP cannot not efficiently deal with rotated images and gives different results after the rotation of the image.

The performance of the descriptor can be increased by increasing the number of the neighbouring pixel. It is observed that if the value of P is increased, the performance of descriptor also improved [15]. The dimensionality of the features grows exponentially with the increase in the number of the neighbours, to reduce this dimensionality existing methods considered only uniform patterns. Those methods are based on the idea that the uniform pattern capture the fundamental structure of texture. In DRLBP shows that the uniform pattern also contain an important information.

Material and methods

LBP follows the fixed arrangement of weights which leads to a rotation variation problem. As the weights are arranged in a circular manner, one single shift can be destroy the whole alignment. The effect of image rotation can be observed by rotating the image which leads to the rotation of image pixels at a particular angle and the angle of rotation cannot be known. To deal with this problem, an adaptive method known as Dominant Rotated Local Binary Pattern (DRLBP) has been applied [15] which computes a reference direction that is used to rotate the image pixels by the same angle with which the image is rotated. The results presented by Rakesh Mehta et.al [15], proved that DRLBP gives best results at different reference directions. In DRLBP method, the dominant direction is defined as the index of neighbourhood pixels whose difference of central pixel with local neighbour is maximum.

In DRLBP, Rotated LBP (RLBP) is very much similar to LBP expression, but one additional mod operator is used in RLBP. Mod operator indicates as modulus operator, it moves the weights circularly to the dominant direction whereas the sequence of weight remains unchanged. In this paper, the same concept has been applied on the skin lesion images using this DRLBP operator to eliminate the problem of rotation variation.

LBP has some significant disadvantages like shows sensitivity to blur and noise of the image and failing to capture texture macrostructure informationto overcome this problem. The MRELBP technique is used. LBP encodes the relationship between neighbour pixels with central pixel whereas MRELBP [14] is designed to encode the distinctive spatial and macrostructure information. It is consist of three LBP like RELBP_CI (central intensity), RLBP_RD (Radical difference) and RELBP_NI (neighbour intensity). The process of RELBP is similar with LBP. The central pixel's intensity act as threshold value. RELBP_NI is average of the neighbouring pixels. Lastly, ELBP_RD is defined as pixel difference in radical directions.

These methods have some limitation like DRLBP, it can be effective on rotation variance but it unable to extract microstructure and macrostructure information from the image, in same as the MRELBP is less efficient on rotation variance, so to overcome this problem, the proposed method is developed.

In proposed method, we have integrated the features of DRLBP and MRELBP. The DRLBP helps in achieving the rotation invariance and MRELBP that helps in calculating microstructure and macrostructure of underline images.

Proposed method

The proposed method achieves rotation invariance as well as it works as a powerful feature extraction descriptor which is applied to classify the skin cancer images. It is an integrated methods which have the properties of both DRLBP and MRELBP methods. This Hybrid descriptor is able to overcome the problem of rotation invariance and it also extractthe useful information from the images, which other descriptor are not able to calculate. The proposed method, firstly extract the information according to DRLBP technique and then it extract the information by using three descriptors of MRELBP like central pixel's intensity, neighbour pixel's intensity and radical pixel difference. Then, the calculated features are combined to find the final feature values. Practically, it has been observed that the hybrid method achieves high results as compared to other LBP extensions. It has attractive properties of strong discriminative-ness, gray scale and rotation invariance.

4. METHODOLOGY USED IN PROPOSED METHOD

The procedure is as follow:

1. Image acquisition-Upload the skin cancer biomedical images as a input in the system.
2. Image Pre-processing-In this stage and Squamous Coloured images are converted into gray scale images
3. Image indexing-In this step, the images are divided into three categories of skin canner which are Melanoma, Basal cell carcinoma and Squamous cell carcinoma.
4. Feature extraction-In this step, features are extracted from the input images by using Hybrid descriptor.
5. Feature classification- In this step, images are classified based on the extracted features using SVM classifier.
6. Performance Evaluation-Last stage is used to evaluate the performance of the proposed method by using three parameters which are accuracy, sensitivity and specificity.

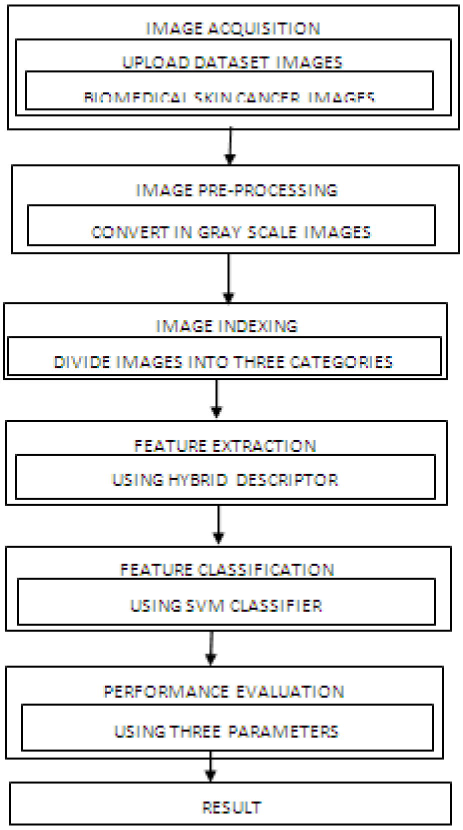

Figure: 1

5. EXPERIMENTAL RESULTS

Experiments are conducted to study the performance of existing LBP variants with the proposed method using the ISIC dataset. Dataset gives the large collection of skin cancer images for testing. These images divided into three categories of skin cancer which are Melanoma, Basal cell carcinoma and Squamous cell carcinoma.

The experiment results are visualized and analysed in the form of graphs for three performance metrics. These performance metrics are sensitivity, specificity and accuracy.

The performance of existing LBP variants and proposed Hybrid descriptor is compared on the basis of these parameter which are mentioned below. These three parameters are determining factors in terms of overall performance of proposed among existing variants of LBP.

5.1 Quantitative parameters

To measure the performance of LBP based variants, we use three different quantitative parameters. These parameters use the term true positive, true negative, false positive and false negative. In testing the case is considered as positive if the feature is correctly matched, otherwise negative if it is unmatched. These terms are as follow:

True positive (TP): The number of cases correctly identified as matched.

True negative (TN): The number of cases incorrectly identified as matched.

False positive (FP): the number of cases correctly identified as unmatched.

False negative (FN): the number of cases incorrectly identified as unmatched.
These terms are used in following parameters:
Firstly, Sensitivity is defined as proportion of positive that are accurately identified. It is also called true positive rate. Mathematically, sensitivity can be expressed as

$$sensitivity = \frac{true\ positive}{true\ positive\ + false\ negative} \quad (2)$$

Whereas, Specificity is defined as measure the proportion of negatives that are accurately identified. It can be expressed as

$$specificity = \frac{true\ negative}{true\ negative\ + \ false\ positive} \quad (3)$$

Lastly, Accuracy is defined as the proportion of true positive and true negative in all evaluated cases. The accuracy of a test is its ability to differentiate the matched and unmatched cases Mathematically, it can be stated as:

$$accuracy = \frac{true\ positive + true\ negative}{true\ positive + true\ negative + false\ positive + false\ negative} \quad (4)$$

5.2 Classifier
The classification is performed using support vector machine (SVM).A support vector machine (SVM) is a discriminative classifier formally based on the concept of decision planes that defines decision boundaries. A decision plane is one that separates between a set of objects having different classes.

TABLE 1: Shows the quantative values of performance evaluation parameters over six LBP extensions and proposed Hybrid descriptor.

PARAMETERS	CANCER TYPE	LBP	CS-LBP	OC-LBP	RLBP	DRLBP	MRELBP	HYBRID
SENSITIVITY	BASAL	**100**	81.81818	**100**	**100**	**100**	87.87879	**100**
	MELANOMA	95.44073	77.81155	79.93921	91.79331	95.44073	73.86018	**95.74468**
	SQUAMOUS	**100**	40	60	**100**	**100**	40	**100**
SPECIFICITY	BASAL	**97.00599**	79.34132	85.02994	95.20958	95.80838	79.34132	96.70659
	MELANOMA	**100**	84.21053	**100**	**100**	**100**	86.84211	**100**
	SQUAMOUS	98.61878	98.0663	95.02762	96.96133	99.72376	94.75138	**99.17127**
ACCURACY	BASAL	97.2752	79.56403	**100**	95.64033	96.18529	80.10899	97.00272
	MELANOMA	95.91281	78.47411	79.93921	92.64305	95.91281	75.20436	**96.18529**
	SQUAMOUS	98.6376	97.2752	60	97.00272	**99.72752**	94.00545	99.18256

As we can see in the table, it is observed that the best classification accuracy sensitivity and specificity are achieved by the proposed approach. As expected the performance of all descriptors drops for this dataset, as the rotation variations and extraction of features makes the classification more difficult. However, the proposed descriptor still outperform than other LBP extensions. The bolded data is highest quantative among all, according to this Hybrid shows best performance.

Accuracy- Figure 2 shows the accuracy of existing and proposed descriptors among three type of cancer.

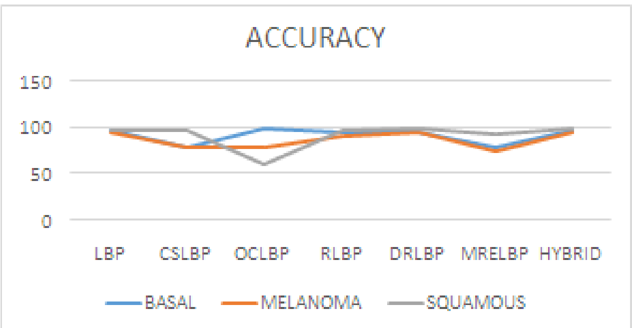

Figure 2

Accuracy level of proposed method is proportion of 100 among three categories of skin cancer. Hybrid descriptor shows highest accuracy in three type of cancer.it is able to find and classify the type of cancer accurately.
Sensitivity-The given Figure 2 compares the existing and proposed method of texture descriptor on the basis of sensitivity. It is clear from the figure that proposed method achieves high sensitivity which is 100% in between three classes of skin cancer.

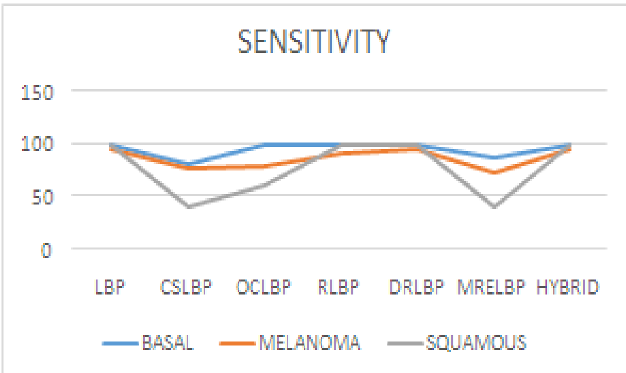

Figure 3

It is clear from the figure that proposed texture descriptor is optimized in term of sensitivity in case of these skin cancer.
Specificity-The given Figure 4shows the specificity level of existing and proposed methods among three classes of skin

cancer, the proposed Hybrid descriptor has highest specificity among three classes.

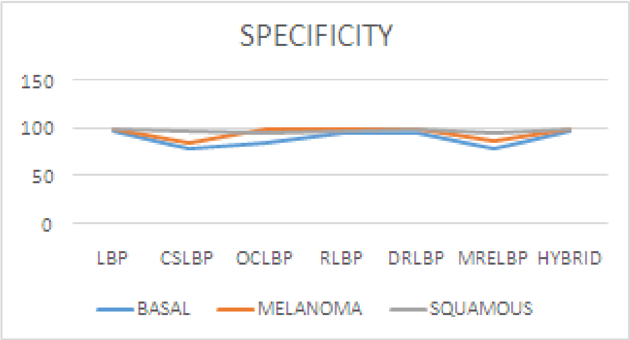

Figure 4

The performance of the proposed approach is compared with LBP based descriptors LBP, CSLBP, OCLBP, RLBP, DRLBP, and MRELBP. Best performance achieved by these descriptor are reported in figure 4. It can be observed that Hybrid also shows outperform result in the case of specificity.

6. CONCLUSION

In this paper, we have introduced a method to classify skin cancer lesion. The performance of proposed method is compared with the existing LBP based texture descriptorsby applying them on standardize database named as ISIC dataset which is a collection of biomedical skin cancer lesion images. The proposed method achieves the rotation invariance and it can efficiently capture the microstructure and macrostructure information. Experimentally, it is analysed that the proposed method has achieved the best quantitative results in terms of quality metrics(sensitivity, accuracy and specificity).

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