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Melanoma Detection Using Modified Extended LBP

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Abstract— Detecting skin cancer at an early age is very crucial for differentiating malignant melanoma from benign one. We presented a novel approach for automatic detection of skin cancer based on modified extended LBP feature. Extended LBP is a generalized form of LBP and we have proposed some modification in its functioning in order to make it more robust. Gabor filter bank is used to segment the lesion area based on the frequency and orientation pattern of the lesion in input image. We have trained and tested our proposed methodology on Support Vector Machine. We have used our own self-created database which consists of 225 images captured from different internet resources. The proposed framework is able to achieve sensitivity, specificity and overall accuracy of about 92.72%, 94.5% and 93.6% respectively.

Keywords— Extended Local Binary Pattern, Modified Extended LBP Gabor filter, Support Vector Machine, Image Segmentation

I. INTRODUCTION

Melanoma is one of the deadliest form of skin cancer that can occur in any body part that contains melanocytes. It occurs primarily due to the over exposure to sun rays. There is a larger probability of having melanoma to fair skinned in comparison to the darker one.

The deadliness of melanoma can be proved as it accounts for merely 4% of all the type of skin cancers but the mortality rate due to melanoma is closed to 75% [1]. Differential diagnosis of melanoma from melanocytic nevi is also posing challenging threat in the diagnosis of malignant melanoma using dermoscopy. It requires trained professionals which can differentiate between them. Hence, automated detection of malignant melanoma can be used as an aid to novice professionals, who can used these automated techniques in order to double validate their diagnostic accuracy.

Computer systems have some limitations and they can't be used as a substitute of humans as several semi-automatic methods such as ABCD- rule, Seven point checklist and Menzies method [2],[3] that have been used in past to increase the diagnostic accuracy of novice dermatologists. These methods require segmentation of tumor which is prone to error as tumor boundary is not regular in shape and restricts the sphere of general automatic segmentation approaches [4]-[7].

Dermoscopic view of diagnosing the malignant melanoma is based on different patterns that appear in the histological structure of tissues. This work is based on extraction of texture features using Modified extended LBP for local one and Gabor features are used for segmentation. Many texture analysis algorithms has been used with the advent of GLCM (Gray Level Co-occurrence Matrix) [8].Computer Aided detection of skin cancer using neural network has been used with overwhelming success in the past. [9]-[11].We have used SVM based model [23,24] for classification of input images into two separate classes of malignant melanoma and melanocytic nevi. The prognosis accuracy of the proposed system is tested on individual basis also.

The paper is organized in the following fashion: part I of the paper discusses about basic introduction to the topic. In Part II we discuss some of the related works in the current field of study. Then in Part III we discuss proposed methodology for the current system. In Part IV, we discuss about results related to current work and compared our results with other methods.

In Part V we elaborate conclusions derived from the results section, and then finally in Part VI we put light on the future scope of current work.

II. RELATED WORKS

Computer aided detection [12] of medical images is an active research area of medical imaging which includes the analysis of digital images in a affected region. A successful CAD system provides useful information for clinical diagnosis. Developing such systems is a challenging task even today.

The texture descriptor proposed in this paper is based on Local binary pattern was first described by T. Ojala et. al.[13][14]. In this paper we have used a modified generalised

version of LBP known as Extended LBP proposed by the Li Liu et. al.[15]. Extended LBP approach is based on the two different features based on pixel intensities and differences between them. The intensity based features takes into consideration the central pixel intensity and those of its neighbourhood called as NE-LBP; whereas, difference based features uses the angular difference known as ROT-LBP. Variance is also calculated known as VAR-LBP. All the three features NE-LBP, ROT-LBP and VAR-LBP are combined into single vector in a row, which is used for training the classifier.

Segmentation of skin cancer plays very important role is accurate classification of disease correctly in the relevant class. Segmentation techniques can be categorised into manual, semi-automatic and automatic. Fully automated CAD systems can be developed using the several low level features such as shape, texture, color. There exists several methodologies that can be helpful in segmenting the lesion area which includes but not limited to as active contours[16], edge detection method[17] ,clustering techniques[18,19] and histogram thresholding [20] method are the name of some.

Classification of inputs based on their extracted features into appropriate class can be achieved by various classifiers [21-22] such as k-NN, Neural Networks, Support Vector Machines, Naïve Bayes etc. In our current work we have used SVM proposed by Vapnik [23,24], which is a binary classifier and supervised in nature. Several other supervised learning methods also exist [24–25] but the reason for choosing the SVM is twofold as it is well known for its generalisation ability which is characterised by its resistance to the problem of over fitting as explained by Vapnik et. al and it also works well for small sized datasets. SVM is based on maximising the margins of separating hyperplanes between two classes.

For measuring the accuracy of the proposed system we have used two objective criteria as sensitivity and specificity.

III. PROPOSED METHODOLOGY

Schematic diagram for our current proposed work is shown in fig. We first give input image into the pre-processing step which enhances the quality of input images and is not affected by the outliers. Then the pre-processed image is given as input into the segmentation step which is based on Gabor filter method. The segmented image is used as input in feature extraction phase which is based on modified extended LBP and finally these extracted features are used to train and test the Support Vector Machine.

3.1Preprocessing

Firstly, dataset of skin cancer images are given as input to our proposed system, then in the second step adaptive median filter is used to filter the noise. After that, in the third step filtered image is given as an input into the segmentation algorithm and segmented image from this step is passed into forth step i.e. the feature extraction phase, in which features are extracted from both the feature descriptors (local and global) feature vectors from these algorithms are combined into single feature vector which is finally passed into the SVM for training and testing purpose.

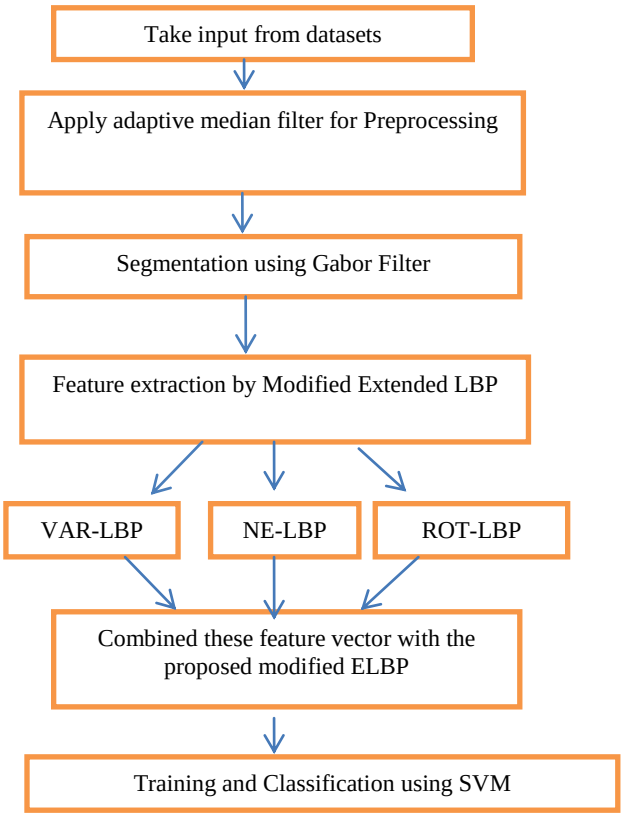
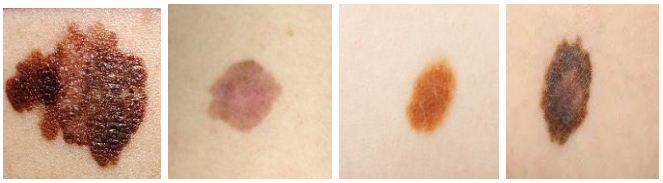


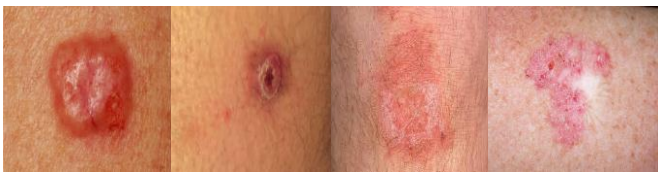
Fig.1. Proposed Methodology

We have used adaptive median filter in place of median filter since adaptive median filters distorts little in comparison to median filter as well as it also removes impulse from an image. Adaptive median filter uses variable size window size based on the median of neighbourhood pixels in the current window; if the median value is the impulse then we need to increase the size of the window size. Central pixel is replaced by the median if it is impulse; otherwise original value of central pixel is retained as it.

Some of the melanoma and non- melanoma skin cancer images are shown in fig.2.



(a) Melanoma images



(b) Non-melanoma images

Figure 2.

3.2 Segmentation

We use the Gabor filter for texture segmentation because it is considered to be a good model of how human distinguish texture therefore this model can show better performance in comparison to other models used for current problem. We have used a simple approach described by A. K. Jain and F. Farrokhnia et. al. In this method a bank of Gabor filters are used to extract information from the input image based on the set of frequencies and orientation of these bank of filters. We have used 4 different orientations between [0 180] at the regular interval of 45 and set of frequencies for each orientations are calculated based on the hypotenuse length of input image. Some post-processing such as Gaussian smoothing and reshaping of feature set is required as required by the PCA and k-means clustering. Processed Gabor features are combined into single cluster using K-means clustering. We have used k=2 one i.e. one for the lesion and one for the skin.

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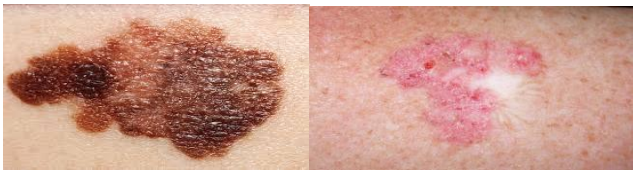
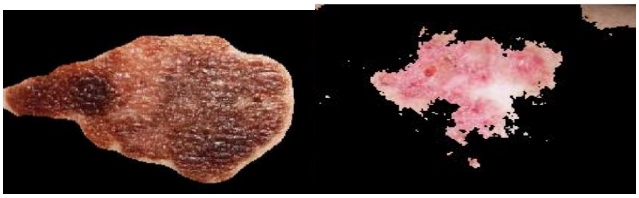


(a) Original images



(b) Segmented Image

Fig 3.

3.3 Feature Descriptor

We have used a fusion of three variations of LBP as feature descriptors for our current work. LBP computes LBP code by taking difference from the central pixel with the neighbourhood pixels, if the value is positive then encoded as 1 otherwise 0, moving in either clockwise or anticlockwise direction. We end up having a binary code which finally gets converted into a decimal number. This process of computing LBP does not end up in recognising unique textural patterns as two different patterns can have same LBP code having different intensities values in neighbourhood. Suppose $x_{r,p}$ represents pixels p situated at distance r from the central pixel. Equ. (1) is used to calculate simple LBP code as:

$$LBP_{p,r} = \sum_{n=0}^{p-1} s(x_{r,n} - x_{0,0}) 2\,\hat{}\,n \qquad s(x)=1, \text{ if } x>=0$$
$$s(x)=0, \text{ if } x<0 \qquad (1)$$

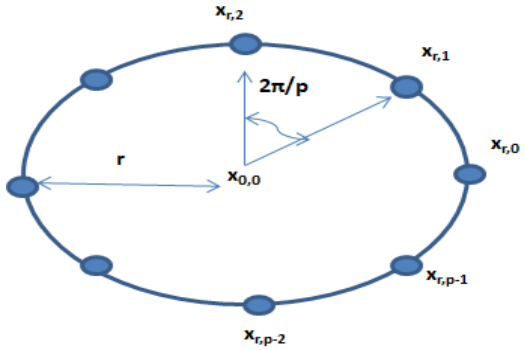


Fig. 3. A central pixel $x_{0,0}$ and its p circularly and evenly spaced neighbors $\{x_{r,i}\}^{p-1}_{i=0}$ on radius r.

So, in order to capture uniqueness of textural pattern we use variance of intensities of neighbourhood w.r.t. central pixel. Two patterns having different intensities values in neighbourhood can end up with same LBP code but the variance of intensity values of these pixels will not be same, since it considers variance of pixel values whereas simple LBP only uses the difference not the actual pixel values. Eua. For calculation of VAR-LBP is as follows:

$$VAR_{p,r} = \sum_{n=0}^{p-1} (x_{r,n} - \mu)\hat{}2$$
$$\mu(average) = \sum_{n=0}^{p-1} X_{r,n} \qquad (2)$$

Now in order to further enhance the differentiating power of LBP another method is used known as NE-LBP. In this method, first difference between the average value and neighbourhood pixel intensities is considered, which results in either 0 or 1 based on the difference whether it is positive or negative. Finally it is converted into single decimal value. Calculation of NE-LBP is done using equ. (3) as follows:

$$NE\text{-}LBP_{p,r} = \sum_{n=0}^{p-1} s(x_{r,n} - \mu) 2\,\hat{}\,n \qquad s(x)=1, \quad x>=0$$
$$0, \quad x<0$$
$$where, \mu(average) = \sum_{n=0}^{p-1} X_{r,n} \qquad (3)$$

NE-LBP and VAR-LBP captures same type of features with some differences:

(i)NE-LBP captures information independent of the intensity values.
(ii)NE-LBP is not rotation invariant whereas, VAR-LBP is rotation invariant. Therefore, we combine both the features as NE-LBP and VAR-LBP.
As NE-LBP and VAR-LBP captures information in horizontal, vertical and diagonal direction. We also use ROT-LBP in combination of NE-LBP and VAR-LBP, in which the pixel value difference between two consecutive pixels situated on radius(r) are taken into consideration. ROT-LBP is compted using equ. (4) as follows:

$$\text{ROT-LBP}_{p,r,\varphi} = \sum_{n=0}^{p-1} s(\varphi) 2 \text{ ^} n$$

Where, s(φ) computes the difference between the values of pixels located at the angular distance of 2π/p.

s(φ) = 1, if difference between two consecutive pixels located at radius r at the angular difference of 2π/p is positive
otherwise, 0 (4)

3.3.1 Modified ELBP

In modified ELBP we have taken the difference of NE-LBP and ROT-LBP values in order to determine the new LBP code. MOD-ELBP=(Difference of mean central pixel and neighbour pixel)-(Difference of values of pixels located at distance 2pi/p at radius r)
The modified-LBP helps in subjugating the net effect of either NE-LBP and ROT-LBP. This MOD-ELBP value is concatenated with combined value of NE-LBP, ROT-LBP and VAR-LBP in order to create new feature vector.
3.4 Pattern classification and testing
We have used support vector machines proposed by Vapnik et. al. [23,24], which are based on the concept of support vectors. Support vectors are the points that lies on boundary of the class and represents whole class. It a class of supervised binary classifiers. Support Vector machine works on the principle that it tries to find hyper-plane by maximises the distance between the support vectors representing two different classes SVM is faster in comparison to Neural Networks since it is based on support vectors and tries to solve the problem of over fitting as well.

IV. RESULTS AND DISCUSSION

This section elaborates the performance of the model proposed by us for detecting malignant melanoma. We have used a considerably large dataset of about 225 images (RGB color space and jpeg format),which we have collected from different online sources (https://www.dermnetnz.org *and* http://www.dermoscopic.blogspot.com). Each image is then resized into 128*128 resolution image. Out of 225 images collected from different online resources 110 are benign and 115 of malignant melanoma type.

In this work, we have used cross validation technique for validation of our system, in which model is not trained with all the data in the datasets, some data is left out for testing purpose. K-fold cross validation technique is more generalised form of cross validation technique in which sample space is divided into k equal sized subspaces and one subspace is used for validation whereas k-1 subspaces are used for training purpose. We have used 4-fold cross validation method in order to access the accuracy of our proposed system. In this method three-fourth of the total images are used for training purpose whereas one fourth of the total images are used for testing purpose. The procedure is repeated several times such that each image is used at least one time for testing purpose. This validation technique is quite useful for small datasets.
Since every methodology is prone to diagnostic errors as it is unable to give 100% classification accuracy therefore some kind of classification accuracy measurement in terms of true and false positives and true and false negatives are used.[27],[28].True positives and negatives are the samples that are classified correctly according to the class they belong to whereas false positives and negatives are the samples which are misclassified into the wrong class and appears as if they are correctly accepted and rejected by the classifier.
Sensitivity and specificity can be computes as
Sensitivity=(TP/TP+FN)*100 --------(5)
Specificity=(TN/TN+FP)*100 -----(6)
Accuracy=(TN+TP/TP+TN+FP+FN)*100 -------(7)
where,
TP (True Positives) = correctly classified positive cases,
TN (True Negative) = correctly classified negative cases,
FP (False Positives) = incorrectly classified negative cases,
FN (False Negative) = incorrectly classified positive cases

	TP	TN	FP	FN	Sens.	Spec.	Overall Accuarcy
LBP (without segmentatio)	41	40	15	14	74	72	73
ELBP (VAR+NE+ROT,without segmentatio)	47	47	7	9	83.9	87.0	85.45
ELBP (with segmentatio)	48	49	7	6	88.8	87.5	88.18
Modified-ELBP(with segmentation using Gabor filter)	51	52	3	4	92.7	94.5	93.6

Table 1. Results of sensitivity (SN), specificity (SP), and accuracy (AC) for the proposed system for skin cancer detection

Melanoma detection
The data reported in the above table exhibits the following important observations:

First of all, considerably high values of sensitivity ,specificity and overall accuracy for our proposed system in comparison with other methods such as simple LBP, ELBP (without-segmentation) and ELBP (with segmentation) is sufficient to prove the worthiness of our system.

Secondly, there are only 3 instances in which benign melanoma are classified as malignant one. These results are quite evident that our proposed system is better for early diagnostic of melanoma.

Thirdly, we have also compared the results of our proposed system with the state some already state of the art proposed systems for the solution of same problem. We find that Sneha et. al in his work[26] of texture analysis for skin cancer detection has used 102 images for testing purpose and achieved the overall occuracy of 92%%, while Elgamal et al [27] has achieved an overall accuracy of 100% using only 20 images for testing purpose, which are quite small in number when compared with our proposed system.

The table shown below shows the comparison of our method with state of the art other methods based on sensitivity, specificity and overall accuracy.

Recently, Zortea et al. [28] presented a technique for the automatic diagnosis of malignant melanoma based exclusively on local pattern analysis with an average specificity and sensitivity of 73%.

Our method has sensitivity of 96.36%,specificity of 94.44% and overall accuracy of 94.49% ,shown in the table 2 below, the overall accuracy of our proposed system is better than earlier proposed systems which comparably less number of training and testing images in the dataset.

	Sensitivity	**Specificity**	**Overall accuracy**
Our method	96.36	94.44	94.49
Elgamal et al	100	95	100
Sneha et al	92.30	91.60	92
Zortea et al.	74	72	73

Table 2. Comparison of our method with other methods.

V. CONCLUSION

In our current work we have proposed used an extended LBP method with some modifications to it in order to make it cover more comprehensive information of the local LBP features. Lesion area is segmented using Gabor filters using texture information, which helps in considerably improving the performance of CAD systems for melanoma detection. The overall accuracy of about 93.6% for our proposed system shows that our proposed CAD system for melanoma detection performs well when compared with the other existing algorithm such as LBP and Extended –LBP.

VI. FUTURE WORK

The future work of our proposed system lies in improving the preciseness and time complexity. There is also scope in improving the texture feature extraction methodology using extended LBP which incorporates more features with less dimensionality.

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Authors Profile

Mr. Ritesh pursued his Master of Technology from IIITM -Gwalior in year 2010. He is currently currently working as Assistant Professor in Department of Computer Science and Engineering, Sri RamSwaroop Memorial University since 2013. His main research work focuses on pattern recognition and medical image processing. He has 7 years of teaching experience.

