CLASSIFICATION OF TYPES OF SKIN LESIONS WITH TASK DECOMPOSITION METHOD

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ABSTRACT

This paper proposes a new concept of computer aided methodology for the classification of skin lesion which is applicable for both melanocytic as well as nonmelanocytic skin lesions. The computer-aided skin lesion classification has drawn attentionas an aid for detection of skin cancers. Several researchers have developed methods to distinguish between melanoma and nevus, which are both categorized as MSL. Till now several researches have been developed only for the detection of melanocytic skin lesion ,but the most common type of skin lesion that occur is basal cell carcinoma and seborirheic keratosis which comes under No-MSL's. Detection of skin cancers is difficult due to the wide variety of skin lesions. Melanomas and nevi are especially difficult to differentiate. It is preferable to deal with these NoMSLs as well asMSLs especially for the potential users who are not enough capable of diagnosing pigmented skin lesions on their own such as dermatologists in training and physicians with different expertise.Therefore our method is suitable to detect all the four types skin lesions (melanoma, nevi, basal cell carcinoma, seborirheic keratosis). We tested our methods on 80 dermoscopy images 20 melanoma,20 nevi,20 basal cell carcinoma and 20 seborirheic keratosis. The results obtained from the flat model is better in the detection of the type of skin lesions. It is preferable to deal with these NoMSLs as well asMSLs especially for the potential users who are not enough capable of diagnosing pigmented skin lesions on their own such as dermatologists in training and physicians with different expertise.

KEYWORD:-*Early detection, Melanocytic, Non-melanocytic, 80 dermoscopy images.*

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1. INTRODUCTION

Occurrence of skin cancer has been increasing over the past few decades and early treatment and diagnosis have become more and more important. For instance five years survival rate melonoma at stage-IV is 9-15% whereas if detected early at stage-II it increases 85-99%[1].Detection of skin cancers is difficult due to the wide variety of skin lesions. Melanomas and nevi are especially difficult to differentiate. Even with dermoscopy, which uses a magnifying glass with a polarization filter and a uniform light source, the accuracy of melanoma accuracy by expert dermatologists remains at 75–84%[4]. However Biopsy provides a definitive diagnosis, it can cause metastasis, and these are invasive operations and make unpleasant experiences to the patient .To avoid unnecessary biopsy, several researchers had been developed non harmful computer-aided methods to distinguish the four types of skin lesions. Our paper consists of three steps: 1) border detection of skin tumor 2) feature extraction 3) classification. Border detection finds the border between the normal cell and the tumor cell. Feature extraction extracts the features of the images such as color statistics , contour shape and texture. Classification process determines the type of skin lesions from the features extracted from the above process. General classifiers such as linear discriminant classifier such as k-NN, artificial neural networks and support vector machines (SVMs)[8] are often used. Based on the above mentioned three steps, we have improved the automated classification methods of the skin lesion types. In above mentioned studies there are several problems:1) only limited types of skin lesions can be applicable for the classification process; 2) the system is not capable in explaining the reasons for the classification results; and 3)The systems were developed and evaluated with only ideal condition images and did not consider the condition of test images. In this paper, we focus on the first issue, mentioned above i.e., the limitation of applicable skin lesion types[13]. Because most of the conventional studies handled only melanocytic skin lesions such as melanomo and nevis where all other pigmented skin lesions come under non-melanocytic skin lesions such as basal cell carcinoma and seborirheic keratosis[15].Eventhough differentiation of NoMSLs is considered to be easier than that of MSLs for expert dermatologists, but it is not always easy for inexperienced dermatologists or physicians with different expertise. Therefore our paper focuses on the classification of the type of skin lesions even by the potential users. We have been working on the development for the classification methods of both MSLs as well as NoMSLs.[17] First, we developed a general border detection algorithm for MSLs and NoMSLs. Since the border of the NoMSLs is often unclear therefore finding the border was a quite challenging job. We further developed a system to detect melanomas from other type of MSLs (nevi) and NoMSLs. Melanoma and BCC accounts for about 80% of all skin cancer incidences. Accurate detection of nevus and SK are clinically significant since they are mostly confused with melanoma types.

1.1 EXISTING SYSTEM

1. Face Recognition: A Literature Survey" by W.ZHAO, R.CHELLAPPA, P. J. PHILLIPS and A. ROSENFELD.

This paper provides an up-to-date critical survey of still- and video-based face recognition research. There are two underlying motivations for us to write this survey paper: the first is to provide an up-to-date review of the existing literature, and the second is to offer some insights into the studies of machine recognition of faces. To provide a comprehensive survey, we not only categorize existing recognition techniques but also present detailed descriptions of representative methods within each category. In addition, relevant topics such as psychophysical studies, systemevaluation, and issues of illumination and pose variation are covered.

2."Removing Non-Uniform Motion Blur from Images," by Sunghyun Cho, Yasuyuki Matsushita and Seungyong Lee

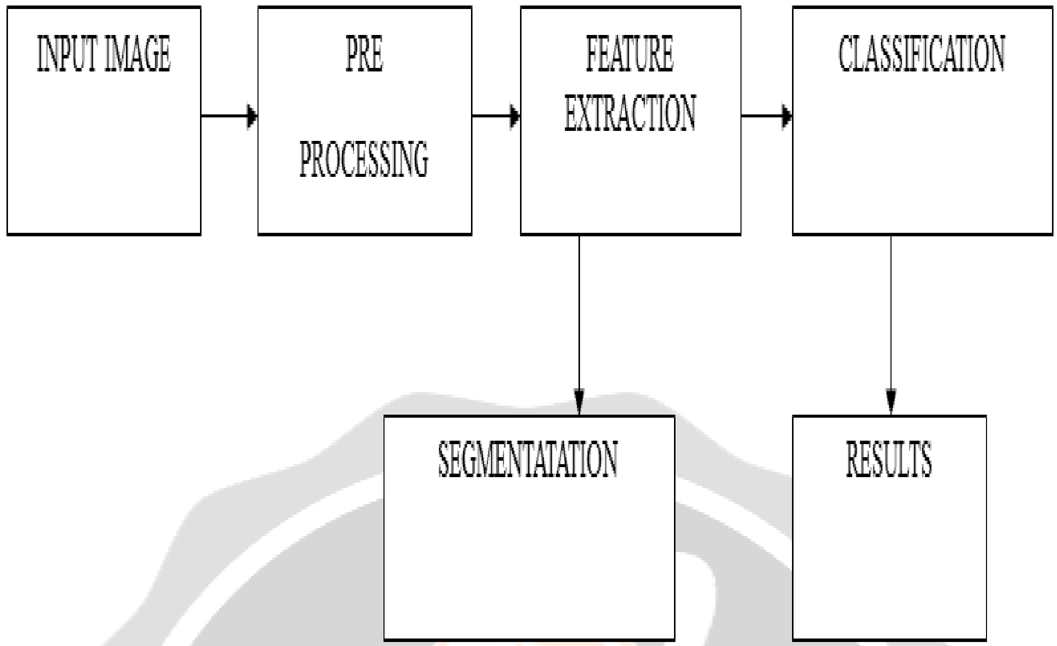
We propose a method for removing non-uniform motion blur from multiple blurry images. Traditional methods focus on estimating a single motion blur kernel for the entire image. In contrast, we aim to restore images blurred by unknown, spatially varying motion blur kernels caused by different relative motions between the camera and the scene. Our algorithm simultaneously estimates multiple motions, motion blur kernels, and the associated image segments. We formulate the problem as a regularized energy function and solve it using an alternating optimization technique. Realworld experiments demonstrate the effectiveness of the proposed method.

3."Removing Camera Shake from a Single Photograph" by Rob Fergus, Barun Singh, Aaron Hertzmann, Sam T. Roweis and William T. Freeman

Camera shake during exposure leads to objectionable image blur and ruins many photographs. Conventional blind deconvolution methods typically assume frequency-domain constraints on images, or overly simpli_ed parametric forms for the motion path during camera shake. Real camera motions can follow convoluted paths, and a spatial domain prior can better maintain visually salient image characteristics. We introduce a method to remove the effects of camera shake from seriously blurred images. The method assumes a uniform camera blur over the image and negligible in-plane camera rotation. In order to estimate the blur from the camera shake, the user must specify an image region without saturation effects.

1.2.PROPOSED SYSTEM

In this paper, we focus on the first issue, i.e., the limitation of applicable skin lesion types. That is, most of the conventional works handled only melanocytic skin lesions (MSLs) such as melanomas and nevi, which originate from melanocytes, whereas nonmelanocytic skin lesions, (NoMSLs) indicating all the other pigmented skin lesions except MSLs such as BCCs and seborrheic keratoses (SKs) have been relatively neglected.



Block Diagram-1:Block diagram of the proposed model.

2. DATASET

In this study, we used 80 digital dermoscopy images categorized into four types: melanoma, nevus, BCC, and SK. The details are given as follows.

1) *Melanoma:* 20 images (10 from Keio University Hospital and 10 from the University of Naples and Graz), a malignant melanocytic tumor (MSL), the most fatal skin cancer.

2) *Nevus:* 20 images (10 from Keio University Hospital

and 10 from the University of Naples and Graz), a benign melanocytic tumor (MSL), often difficult to differentiatefrom melanomas.

3) *BCC:* 20 images (10 from Keio University Hospital and10 from TokyoWomen'sMedical University), a malignant nonmelanocytic tumor (NoMSL), the most common skin cancer.

4) *SK:* 20 images (10 from Keio University Hospital and 10 from TokyoWomen's Medical University), a benign nonmelanocytic tumor (NoMSL), which commonly occurs in the elderly and is sometimes confused with melanomas.

These images have different resolutions ranging from 512 × 384 to 3641 × 2732. The diagnosis of the skin lesions was determined by histopathologicalexamination or clinical agreement by several expert dermatologists.

3. METHOD

3.1. Border Detection

From each choosen skin lesion image, we have extracted the border between the tumor and the surrounding normal skin area. More the accurate border detection more the accuracy of classification. Pervisouly available computer aided methods of border detection mainly focuses on only melanocytic skin lesions (MSLs). In our paper, we developed a general border detection algorithm which is applicable for both MSLs and NoMSLs. The important part of the algorithm is color thresholding, removal of artifacts such as microscope border and hair on the affected area, and inclusion of bright area seen especially in NoMSLs types. The algorithm performed here outperformed other perdetermined methods like (dermatologist-like method , SRM , hybrid thresholding , *k*-means++, and JSEG)even for NoMSLs the algorithm showed equivalent or better performance for MSLs.

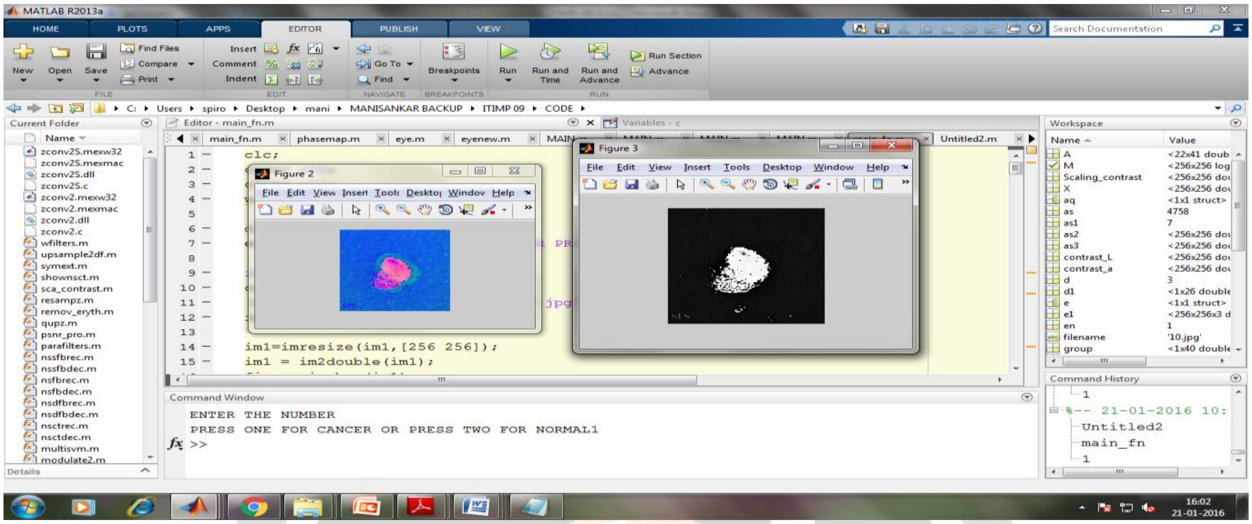


Fig-1:Output of the image after border detection

3.2 Feature Extraction

Once determination the border of the tumor is over, we segmented the skin lesion image into four regions as normal skin, peripheral, central tumor, and whole tumor. The whole tumor consists of all pixels within the extracted border of the skin lesions.In contrast, the normal skin is all pixels on the outside of the border. The peripheral region is the first 30% of the whole tumor area, obtained by going inward from the border. Finally, the central tumor is obtained by removing the peripheral from the whole tumor. For preprocessing, we have rotated the images to make the major axis of the whole tumor parallel to its horizontal axis (*X*-axis).We have also resized the images such that the major axis of the whole tumor was 512 pixels in length. Main aim of resizing the images is to reduce the computing time during execution steps.Once the preprocessing is over we have calculated the candidate images features. The candidate image features have been grouped into three types color, subregion, and texture.

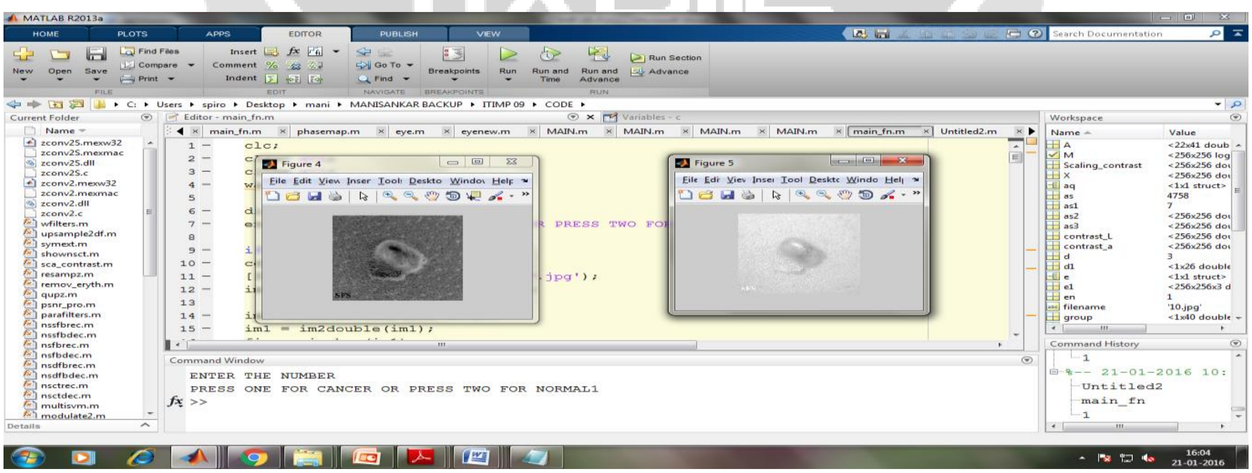


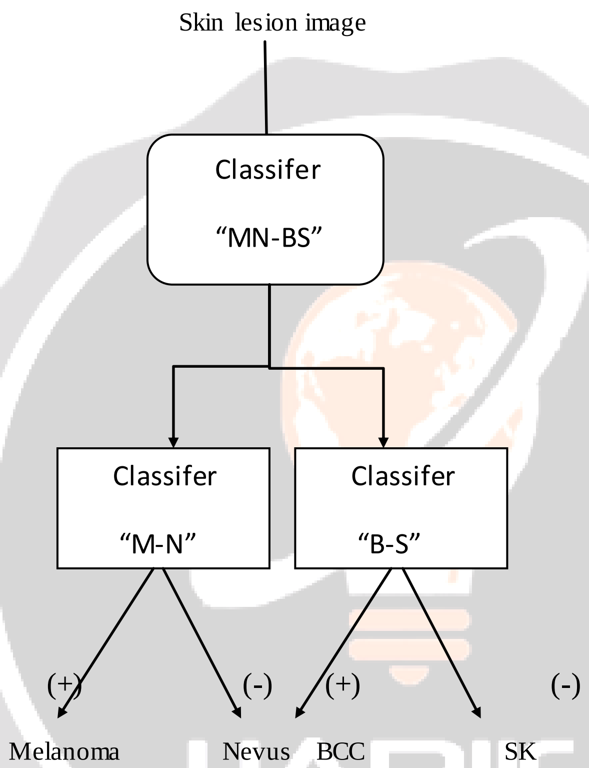
Fig-2:Output of the image after feature extraction

4. Classification

There two types of classifiers used here one is layered model and another one flat model. Layered model is used as the primary classification model and flat model is used as the performance baseline.

4.1 Layered model

The classifier initially has a predetermined value called as threshold. When the input skin lesion image value is greator than the threshold value it is identified as MSL's(+). Otherwise the image is displayed as No-MSL's(-).



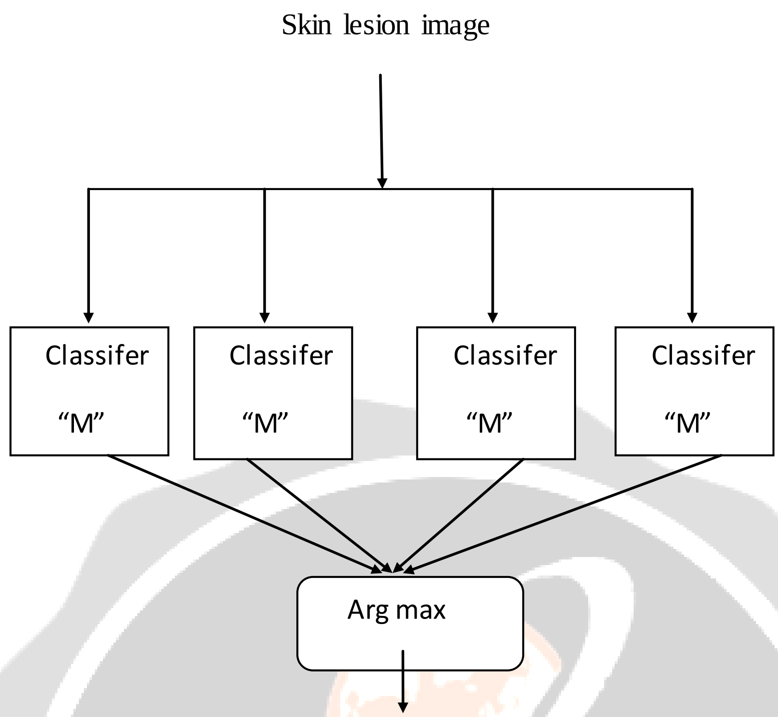
Block Diagram-2:Block diagram of the layered model.

4.2 Flat model

We two types of flat models flat model 1 and flat model II as performance baseline. Each of them have four linear classifiers namely: "M" , "N" , "B" , "S".Such type of classificaton model is used in muticlass classification. *Fi* is calculated to compare the outputs of the four classifiers

$$\boxed{Fi = \alpha i \times (Oi - \xi i).}$$

Here *Oi* is the normalized output value of the classifier *i*. ξi and αi are the threshold and scaling factor value respectively.



Block Diagram-3: Block diagram of the flat model.

5. RESULTS

Once all the above mentioned steps are over final output is obtained which clearly specifies the type of skin lesion present in the given input image with help of the information extracted from previous steps.The snapshot of the final output specifying a type of skin lesion(BCC) is available.

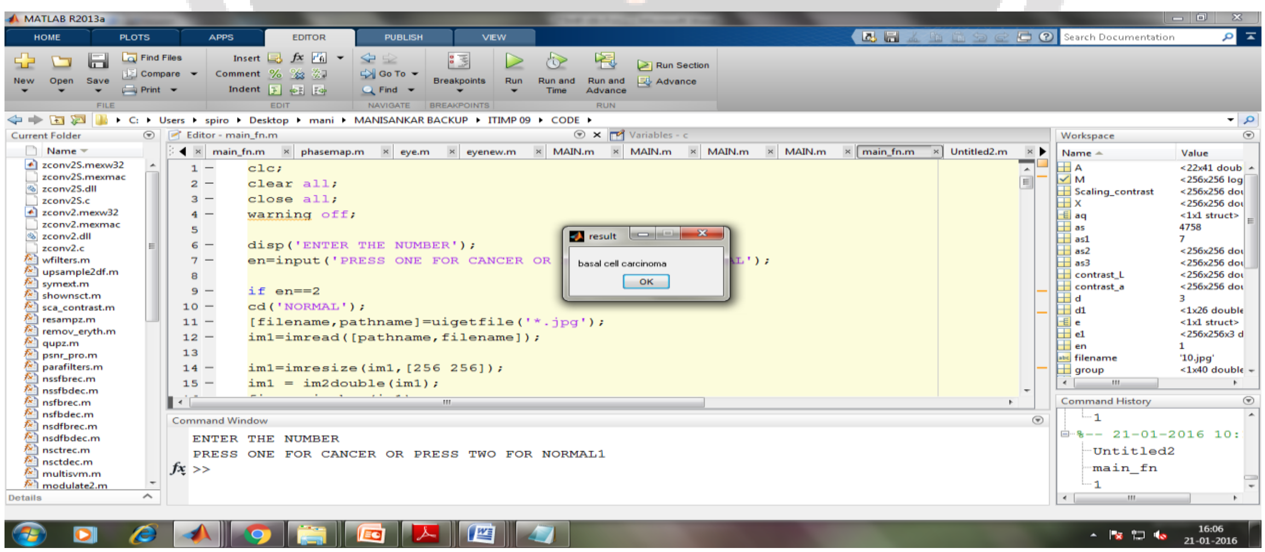


Fig-3:Final output

6. CONCLUSION

This system is an efficient way of classifying skin lesions. It classifies all the four types of lesions such as melanoma, nevi, basal cell carcinoma, seborirheic keratosis. This provides the simplest method to do the same and the time constraint is very less. The performance of the classifier is measured to be around 95% and is the most accurate and efficient method proposed till date.

7. REFERNCES

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