

Automated Melanoma Detection Using Sparse Classifier and Feature Selection Based T'test Method

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Abstract—Melanoma is also referred as malignant melanoma, which is a type of skin cancer and it is developed from the pigment-containing cells which are known as melanocytes. High-level features are needed in the existing method because low classification accuracy occurs. In order to improve existing methods sparse representation method is used. Image analysis tasks are carried out by sparse representation classification and is a pixel-wise classification of images. Image pixels can be classified by sparse classifiers. High classification accuracy can be obtained using the sparse method. T'test method is used when the variances of two normal distributions are unknown and use a small sample size. It examines with two samples whether it is different or not. The results show the accuracy of the proposed recognition system and high sensitivity in melanoma recognition using sparse classifiers and T'test method.

Keywords—Cold challenge, Texture features, Principal component analysis, localization of abnormality, skin cancer, Texture, Malignant.

I. INTRODUCTION

Most pigment cells are found in the skin. Melanoma is a form of skin cancer that arises when pigment-producing cells known as melanocytes mutate and become cancerous. It can be dangerous because it is more likely to spread. Melanoma is just one type of skin cancer. It can also occur in the eyes and other parts of the body, including, rarely, in the intestines. It is mostly not affected people with darker skin. It is common for skin cancer cells such as basal cell and squamous cell, but Melanomas can develop anywhere on the skin. Other common regions are the neck and face. First, it is difficult to segment lesion areas which are a low contrast between skin lesions and normal skin. Second, there is a high degree of visual similarity between melanoma and non-melanoma lesions and it is difficult to distinguish melanoma lesion from non-melanoma lesion. Third, if there is any variation of skin conditions, e.g. skin color, natural hairs or veins, in terms of color and texture, etc. are difficult. In men, it is affected in the chest and the back. In women, it is mostly affected in the legs. Melanoma from dermoscopy images is a difficult task and it has several challenges. Skin lesion segmentation is the foremost step for this classifications.

A. How cancer develops-

Initially, Skin cancer will develop in skin tissue, and it is a very challenging task [3]. The variation of melanomas is occurring in color, shape, size and location of skin. In the dermoscopy images, there is a high degree of similarity between melanoma and non-melanoma lesions. It is difficult to discriminate melanomas from non-melanoma skin lesions and the factors that developing skin cancer include:

- Prior History of Skin Disease
- Family History of Skin Disease
- Age
- Race
- Reproductive and Menstrual History
- Radiation Exposure
- Dietary Factors

It is very difficult to determine with accuracy at this time [4]. The probability of breast cancer is increasing with age and risk factors associated with the development of skin cancer.

II. METHODOLOGIES TO DETECT SKIN CANCER

Various techniques are available to detect the presence of skin cancer nowadays. Based on different sources as given below:

- Based on Radiography
- Based on endoscopy
- Based on magnetism-MRI

Other sources are attenuation, microwave, x-rays, nuclear, electrical impedance, computer modelling-inverse simulation [5]. Radiography is the two most widely used skin screening tools.

A. Radiography

Radiography uses radiation to provide images of the tissues, organs, bones, and vessels that were in the human body. Radiologists, physicians had special training in interpreting diagnostic images, read or diagnose these images. Treatment of a patient depends on the accurate and precise production of radiographic images. Two types of radiographic images are projection radiography and fluoroscopy. The creation of images can be exposed to an object of X-rays or any other high-energy forms of electromagnetic radiation and capture the resultant remnant beam is known as projection radiography. Fluorescent screen is used to convert the shadow to light which is then captured on photographic film, it may be captured by a phosphor screen to be "read" later by a laser. Fluoroscopy produces real-time images of internal structures of the body which is similar to radiography and employs x-rays, as a lower dose rate. Air, barium, and iodine, are used to visualize internal organs.

B. Medical imaging

Medical imaging is defined as the technique in which it is created visual representations for the interior part of a body for clinical analysis and medical intervention. Medical imaging reveals internal structures hidden by the skin and bones, and also diagnoses and treats disease. Medical imaging is a database of normal anatomy and physiology to make it identify abnormalities. Imaging of removed organs and tissues can be performed for medical reasons, such as a part of pathology is used instead of medical imaging. It uses X-ray radiography technique, magnetic resonance imaging, and nuclear medicine imaging techniques as positron emission tomography.

C. Magnetic Resonance Imaging –

Magnetic resonance imaging is a medical imaging technique and it is used in radiology to form pictures of the anatomy. MRI scanners use strong magnetic fields, and radio waves to generate images of the organs in the body. It does not involve X-rays and the use of ionizing radiation, and it can be distinguished from CT or CAT scans. Magnetic resonance imaging is a medical application of nuclear magnetic resonance (NMR). NMR can also be used for imaging and NMR applications are NMR spectroscopy etc.

III. PROPOSED METHOD SYSTEM METHODOLOGY

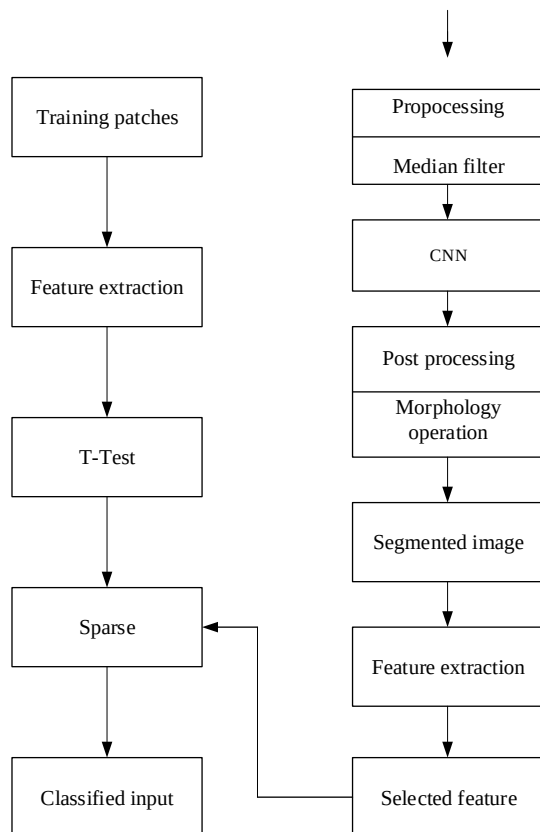


Fig 1: Block Diagram of Proposed System

A. Sparse classifier

Sparse classifier estimates such as irrelevant or redundant components of skin are exactly zero. Sparseness is a desirable feature in classifier learning. The degree of sparseness and performance increases by using N kernel classifiers. Sparseness is a structural simplification of the estimated function to integrate application-specific properties. We proposed a generalized ridge term with β [6]. The power of stems from the generalized ridge term enables penalization of differences in weights between defined features, which should be similar to reflect their associations. It is penalizing the differences in successive weights of ordered features and in the context of regression, for modelling correlations between adjacent pixels in image analysis.

B. T-test Method-

The most common type of t-test is often used to assess two classes which are statistically different from each other and by calculating a ratio between the difference of two class means and the variability of two classes. The t-test has been used to rank the features of microarray data. The t-test is limited to two-class problems. For multi-class problems, for each gene, first, calculate the t-statistics value and then evaluate the difference between the mean each class, where the difference between each class is standardized by the standard deviation.

IV. RESULT

In figure 1 input image which is the melanoma affected image is given in figure 2 input image is converted to a grayscale image. In figure 3 normalization process is done in which it changes the range of pixel intensity values. In figure 4 morphological process image is given. It processes the images based on shapes. In figure 5 segmentation is done using sparse classifier method. Finally affected area is selected by T'test method

Input Image



Fig: 2 Input image

Grayscale Image

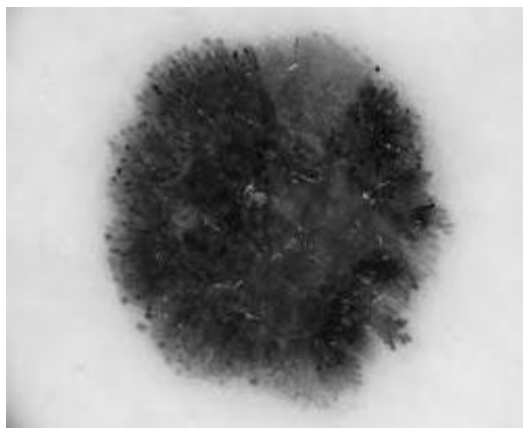


Fig.3 Grayscale image

After Normalization

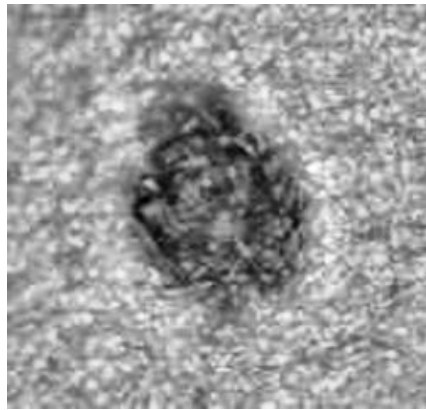


Fig.4 Normalization

After Morphology preprocess

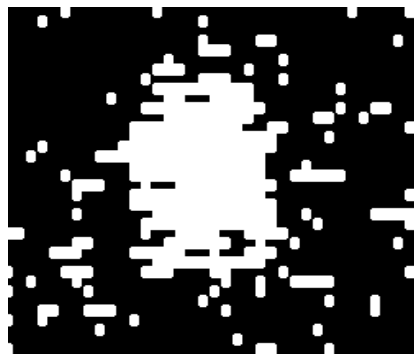


Fig.5 Morphology pre-process

Segmented Region

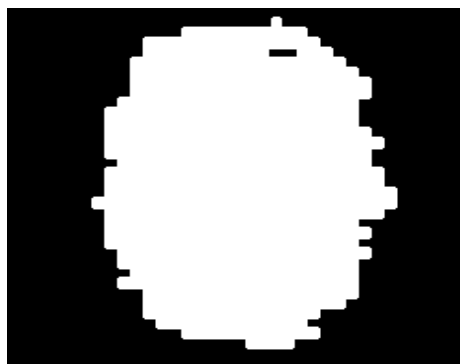


Fig.6. Segmented Region

ROI Image



Fig.7. ROI Image

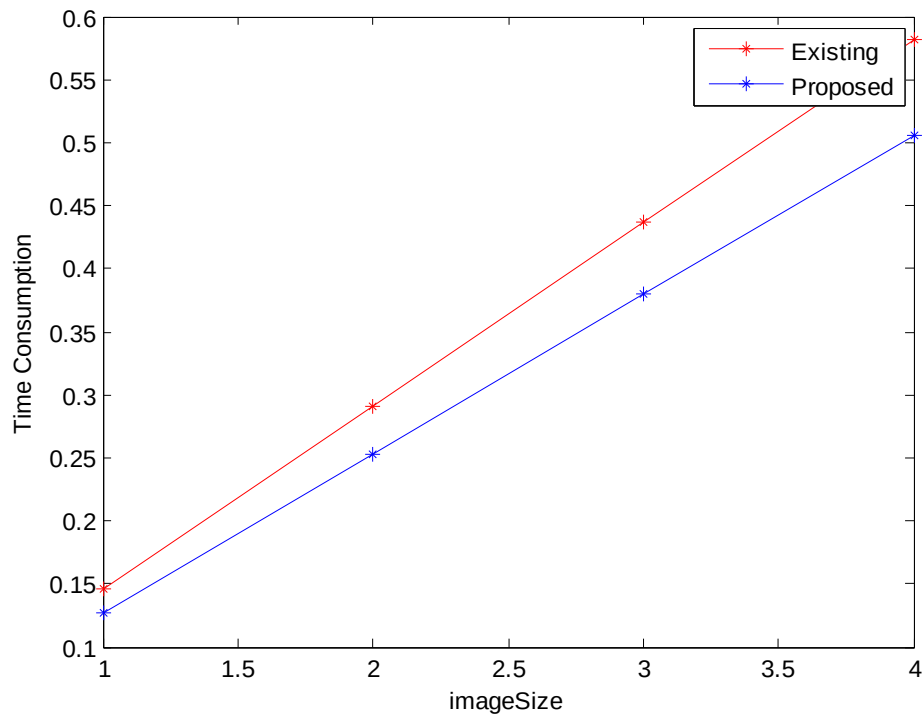


Fig. 8 Comparison chart between existing and proposed method

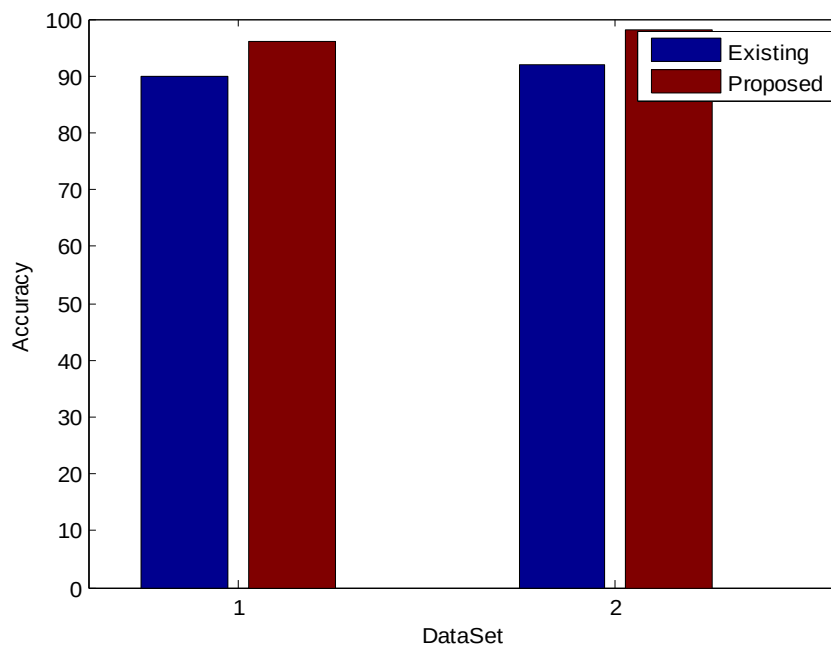


Fig.9 Accuracy estimation

V. CONCLUSION

The method based on very deep CNN to meet the challenges of automated melanoma recognition in dermoscopy images, which consists of two steps: segmentation and classification. We seamlessly connect the two steps and form an automated framework without the need for manual interaction. Compared with much shallower counterparts, the very deep CNN's can generate features with high discrimination capability, and hence improve the performance of both segmentation and classification tasks. We further construct a novel FCNN for accurate skin lesion segmentation. Extensive experiments conducted on the open challenge dataset of Skin Lesion Analysis. Towards Melanoma Detection in ISBI 2016 demonstrated the effectiveness of the proposed method.

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