GRD Journal for Engineering | Volume 3 | Issue 5 | April 2018
ISSN: 2455-5703

Classification of Melanoma Thickness from Dermoscopic Images using Mobile Devices

Dr. B. Muthusenthil
Associate Professor
Department of Computer Science & Engineering
Valliammai Engineering College, Tamil Nadu, India

Ravishanker S
Student
Department of Computer Science & Engineering
Valliammai Engineering College, Tamil Nadu, India

Sivaraman V
Student
Department of Computer Science & Engineering
Valliammai Engineering College, Tamil Nadu, India

Srinath R. M
Student
Department of Computer Science & Engineering
Valliammai Engineering College, Tamil Nadu, India

Abstract

The survival of patients with melanoma is mainly dependent on the thickness of the melanoma. The depth of the melanoma is usually give in millimeters then calculated using pathological examination following a biopsy of the suspected lesion. To avoid invasive methods in the estimation of the thickness of the melanoma prior to surgery we propose a computational image analysis system from dermoscopic images. A recent interpretable method merging logistic regression along with artificial networks (LIPU) logistic regression using initial variables and product units, which are nominal classification methods, are compared in terms of performance. In case of binary classification LIPU performs with an accuracy of 77.6% compared to all other methods while in case of the second scheme the ordinal classification methods achieve a better balance between the performances of all classes even though LIPU reports the highest overall accuracy.
Keywords- Melanoma, Dermoscopic Images, Image Analysis, Classification Methods

I. INTRODUCTION

MELANOMA is a malignancy of melanocytes, the cells which produce the pigment melanin that colors the skin, hair and eyes. Melanoma that occurs on the skin, called cutaneous melanoma, is the most common type of melanoma. It is well accepted that only early detection can reduce mortality, since the prognosis of patients with melanoma depends on the thickness of the tumor at the time of surgical treatment.

II. EFFECTS OF MELANOMA

Melanoma is classified into 2 stages keeping in consideration the depth of the primary tumor and how far the cancer has spread from the initial point.
The staging system of melanoma is fundamental in identifying the best treatment method for single cases and to predict the prognosis. Insitu melanomas have a good prognosis following surgery with adequate surgical margin. Invasive melanomas have bad prognosis.
Breslow thickness indicates the depth of the melanoma calculated perpendicularly from the skin surface, especially form the stratum granulosum of the epidermis to the lower most level of melanoma (in mm)

III. OUR SYSTEM DIAGNOSTICS

We propose a computational image analysis system from dermoscopic images to prevent the use of an invasive method in the calculation of thickness of melanoma before surgery. The clinical findings that correlate particular characteristics present in dermoscopic images and tumor depth is the basis of the proposed feature extraction

IV. LITERATURE SURVEY

P. Guti´errez et al [1] proposes that Ordinal regression problems are those machine learning problems where the objective is to classify patterns using a categorical scale which shows a natural order between the labels. Many real-world applications present this labelling structure and that has increased the number of methods and algorithms developed over the last years in this field. Although ordinal regression can be faced using standard nominal classification techniques, there are several algorithms which can specifically benefit from the ordering information. Therefore, this paper is aimed at reviewing the state of the art on these techniques and proposing taxonomy based on how the models are constructed to take the order into account

Rahil Garnavi et al [2] proposes a novel computer-aided diagnosis system for melanoma. The novelty lies in the optimized selection and integration of features derived from textural, border based and geometrical properties of the melanoma lesion.
Bing-Yu Sun et al [3] proposes we propose a novel regression method by extending the Kernel Discriminant Learning using a rank constraint. The proposed algorithm is very efficient since the computational complexity is significantly lower than other ordinal regression methods. We demonstrate experimentally that the proposed method is capable of preserving the rank of data classes in a projected data space.

Aurora Sáez et al [4] presents different model-based methods of classification of global patterns in dermoscopic images are proposed. Global patterns identification is included in the pattern analysis framework, the melanoma diagnosis method most used among dermatologists. The modeling is performed in two senses.

P. Cavalcanti and J. Scharcanski et al [5] proposes the classification of melanocytic skin lesions is a very difficult task, and usually computer-aided diagnosis systems or screening systems focus on reproducing medical criteria as the ABCD rule. However, the texture information can also contribute significantly for the lesion classification, since malignant cases tends to present texture patterns different from benign cases. In this chapter, we detail five representative sets of features that have been proposed in the literature for the representation of melanocytic lesions texture information, and then we analyze how these features distinguish between malignant and benign classes using two well-known classifiers.

M. EmreCelebi et al [6] Dermoscopy improves melanoma recognition, but most criteria were described in the context of superficial spreading melanoma. The objective is to test whether pigmented nodular melanoma could be recognized dermoscopically by the presence of a combination of blue and black colour within the lesion.

Dermoscopic images of histopathologically diagnosed pigmented nodular tumours with no (or only minimal) flat component were evaluated for the presence of standard melanoma criteria and for the presence of a new feature named blue-black (BB) colour. Sensitivity, specificity, positive predictive value and negative predictive value were calculated for standard criteria and BB feature in relation to the diagnosis of melanoma and to diagnosis of malignancy.

S. Jeyalakshmi1 and R. Radha et al [7] proposes a diagnostic system using digital image processing would diagnose the deficiency symptoms much earlier than human eyes could recognize. This will enable the farmers to adopt appropriate remedial action in time. This paper focuses on the review of work using image processing techniques for diagnosing nutrient deficiency in plants

Pablo G. Cavalcanti et al [8] proposes the texture information can also contribute significantly for the lesion classification, since malignant cases tends to present texture patterns different from benign cases. In this chapter, we detail five representative sets of features that have been proposed in the literature for the representation of melanocytic lesions texture information, and then we analyze how these features distinguish between malignant and benign classes using two well-known class.

A. K. Kureshi et al [9] proposed that even after intensive training, and thus, impede the efficient monitoring of the disease. Hand radiograph analysis is difficult for radiologist as there are 14 number of hand joints. To avoid observer dependency, computer-aided analysis is required. Wrist joint space narrowing is a main radiographic outcome of rheumatoid arthritis (RA). Yet, automatic radiographic wrist joint space width (JSW) quantification with statistical properties for RA patients has not been widely investigated. The automated analysis of statistical properties helps to reduce need of skilled personnel.

L.Li et al [10] proposes to assess the diagnostic accuracy of dermoscopy for the diagnosis of melanoma compared with naked eye examination by performing a meta-analysis exclusively on studies performed in a clinical setting. The selected studies compare diagnostic accuracy of dermoscopy with naked eye examination using a valid reference test on consecutive patients with a defined clinical presentation, performed in a clinical setting.

Geert Litjens ThijsKooiBabak et al [11] proposes Deep learning algorithms, in particular convolutional networks, have rapidly become a methodology of choice for analyzing medical images. This paper reviews the major deep learning concepts pertinent to medical image analysisand summarizes over 300 contributions to the field, most of which appeared in the last year. We survey the use of deep learning for image classification, object detection, segmentation, registration, and other tasks. Concise Garcia et al [12] proposed a method for automatic bone boundary detection in hand radiographs by using an adaptive snake method, but it doesn’t work for those affected by RA. The level set method has advantages over the snake method. It however often leads to either a complete breakdown or a premature termination of the curve evolution process, resulting in unsatisfactory results. For those reasons, we propose a modified level set method for detecting bone boundaries in hand radiographs affected by RA. Texture analysis is also applied for distinguishing the hand bones and other areas.

V. PROPOSED SYSTEM

A. System Architecture

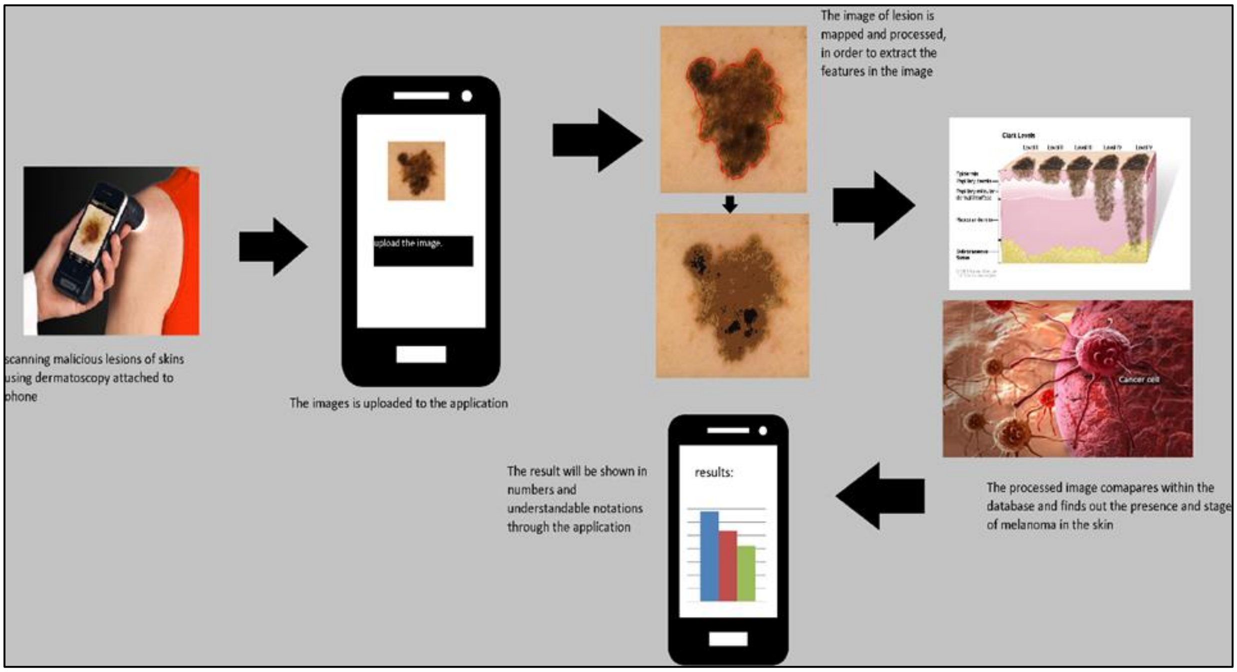


Fig. 1: System Model

B. System Working

1) The user should take a photo of the region suspected of melanoma.
2) The photo is to be uploaded to the application.
3) The given image will be processed and their features will be extracted in order to compare it with the image in the database.
4) The result will be shown implementing the presence and stage of melanoma in understandable notations

C. UML Diagram Representation

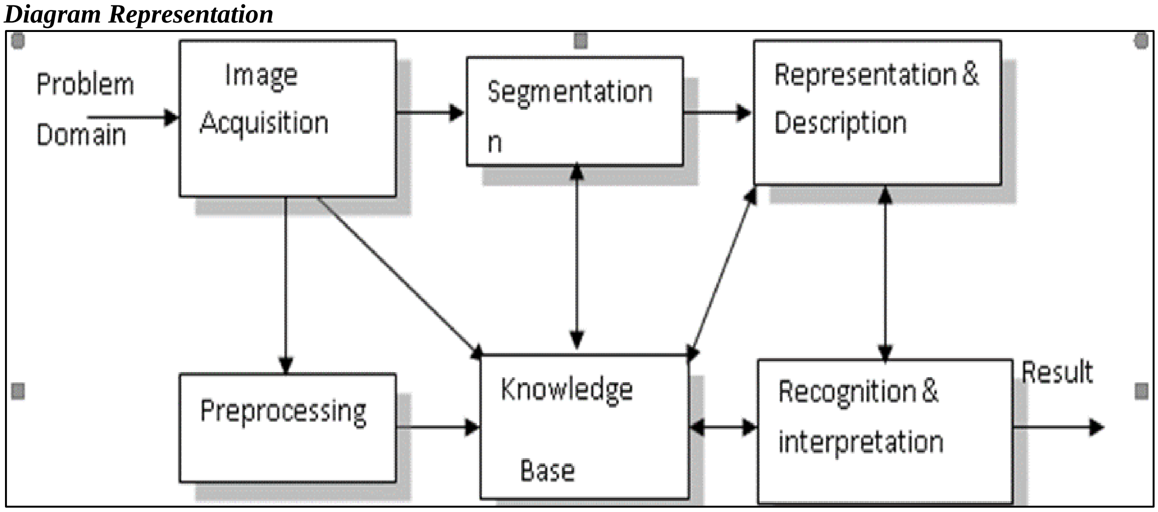


Fig. 2: Working Interaction Model

D. Methodologies

1) Module 1: Preprocessing

The input is a RGB color image, since we need to extract gray level features we need to convert the image to gray. This process converts the RGB color image to gray by using the formula given below,

$$Gray = 0.2989*R + 0.5870*G + 0.1140*B$$

Where, R is the red intensity channel, G is the green intensity channel and B is the blue intensity channel.

2) Module 2: Segmentation

The next step after preprocessing is to segment the region of interest. This is done by converting the image to binary. Since the intensity of the cancer area will be less compared to the intensity of the skin colour. Hence a very low threshold value can be used to find the correct mask for the segmentation of the region of interest.

3) Module 3: Feature Extraction

After extracting the region of interest we need to extract the features to classify the stages. Since each stages of cancer will have variations in features. We find different features and combine them in to a single vector.
We find different feature extraction methods and these methods are as follows,

a) Shape features,
b) Color features,
c) Pigment network features,
d) Texture features.

4) Module 4: Classification

Our main aim is to classify the various stages of skin cancer. We use two different classification methods. First one is binary classification method where we find the two stages in skin cancer. They are thin and thick stages. In the second classification method we find the three stages of cancer they are thin, intermediate and thick stages. The two classification methods are as follows,

1) Logistic regression using Initial Variables and Product Units (LIPU)
2) Ordinal classification

VI. MODULE FLOW

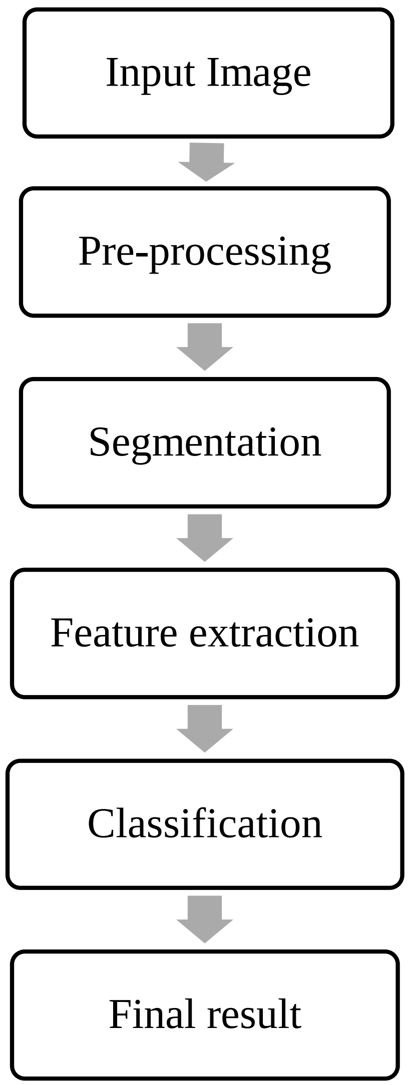


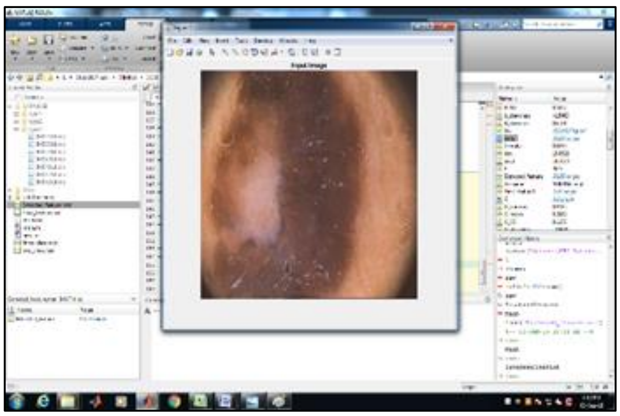
Fig. 3: Model Flow Diagram

VII. EXPERIMENTAL RESULTS

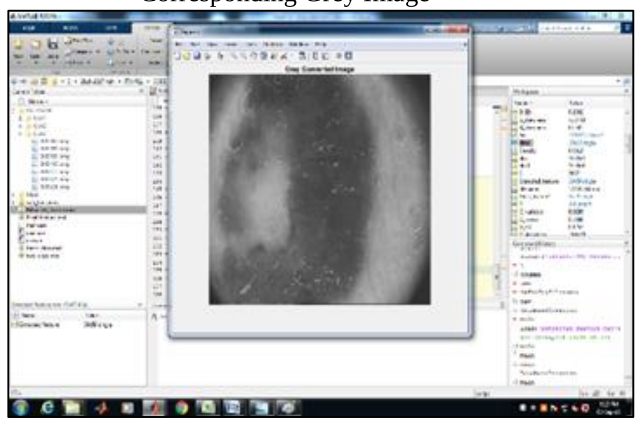
Capturing the Image

First the image is captured from mobile device

Input Image

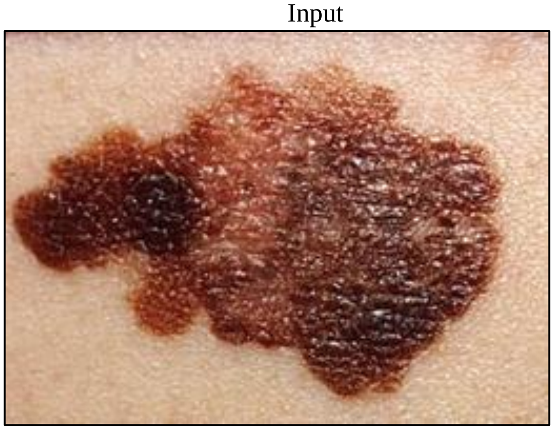


Corresponding Grey Image



The input image is then converted into corresponding grey scale image for further processing

Input



Mapping Lesion of Lesion

The output image is then processed to grey scale conversion and mapping of the lesion area to differentiate the stage.

The mapped lesion .bmp images are then run through the database to match with the suitable stage predefined in the database

Image comparison with the database.

VIII. RESULTANT OUTPUT

Finally the output is produced through an .exe format as a dialog box

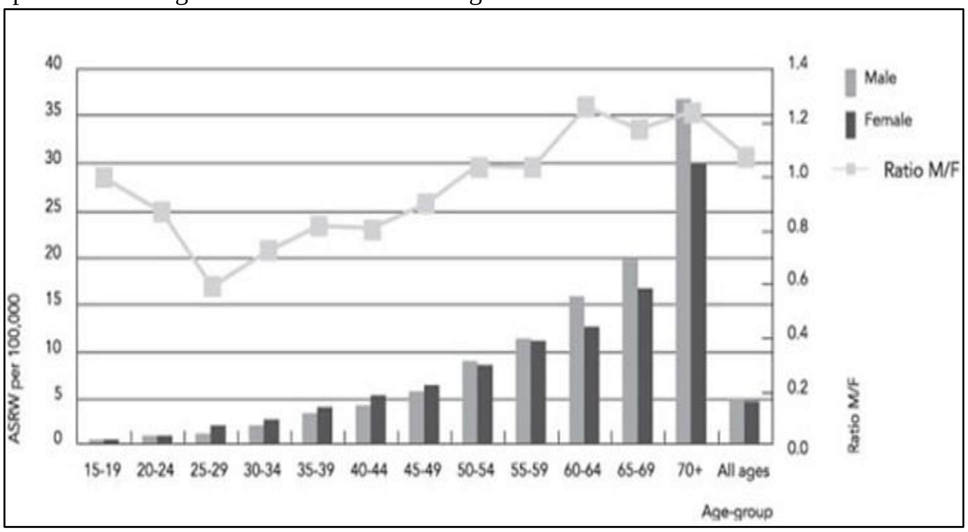


Fig. 5: Statistical Report of Gender Analysis – Melanoma

The above graph represents the variation of lesions in both genders, male and female.

IX. CONCLUSION

The main advantage of LIPU method is that is an interpretable model, which also provides probabilistic classes assignment and performs feature selection during the learning phase. In this sense, a study of how the features contribute to the classification model is presented. All features were present in the 10 models, either in the linear part or interacting with others in the basic functions (non-linear part of the model). However, some of them present a greater relevance because they are included individually in the majority of the models. This is the case of features related to black and blue colors, pigment network, homogeneity and some texture features extracted from three approaches proposed. In spite of some authors findings which indicate that shape features, red color associated to vascular pattern and white color associated to white scar-like areas can be relevant, in our system, these features do not have an individual influence in the linear part, although they do interact with others on the basis functions.

REFERENCES

[1] P. Guti´errez, M. P´erez-Ortiz, J. S´anchez-Monedero, F. Fernandez- Navarro, and C. Herv´as-Mart´inez, "Ordinal regression methods: survey and experimental study," IEEE Transactions on Knowledge and Data Engineering, vol. In press, no. 99, 2015.

[2] Bag-of-Features Classification Model for the Diagnose of Melanoma in Dermoscopy Images Using Color and Texture Descriptors Catarina Barata1, Jorge S. Marques1, and Teresa Mendon¸ca2 M. Kamel and A. Campilho (Eds.): ICIAR 2013, LNCS 7950, pp. 547–555, 2013.c Springer-Verlag Berlin Heidelberg 2013

[3] Texture Information in Melanocytic Skin Lesion Analysis Based on Standard Camera Images, Pablo G. CavalcantiJacobScharcansk Part of the Series in bioengineering book series (SERBIOENG) 27 September 2013

[4] Evaluation of cutaneous melanoma thickness by digital dermoscopy analysis: a retrospective study. Rubegni P1, Cevenini G, Sbano P, Burroni M, Zalaudek I, Risulo M, Dell'Eva G, Nami N, Martino A, Fimiani M Melanoma Res. 2010 Jun;20(3):212-7. doi: 10.1097/CMR.0b013e328335a8ff

[5] P. Cavalcanti and J. Scharcanski, "Texture Information in Melanocytic Skin Lesion Analysis Based on Standard Camera Images," in Computer Vision Techniques for the Diagnosis of Skin Cancer, J. Scharcanski and M. E. Celebi, Eds. Springer Berlin Heidelberg, 2014, pp. 221–242.

[6] G. Argenziano, C. Longo, A. Cameron, S. Cavicchini, J.-Y. Gourhant, A. Lallas, I. McColl, C. Rosendahl, L. Thomas, D. Tiodorovic-Zivkovic, P. Zaballos, and I. Zalaudek, "Blue-black rule: a simple dermoscopic clue to recognize pigmented nodular melanoma," British Journal of Dermatology, vol. 165, no. 6, pp. 1251–1255, 2011.

[7] A review on diagnosis of nutrient deficiency symptoms in plant leaf image using digital image processing s. jeyalakshmi1 and r. radha2, ictact journal on image and video processing, May 2017, volume: 07, issue: 04

[8] Computer-Aided Diagnosis of Melanoma Using Border and Wavelet-Based Texture AnalysisGarnavi R, Aldeen M, Bailey J IEEE Trans InfTechnol Biomed. 2012 Nov; 16(6):1239-52. doi: 10.1109/TITB.2012.2212282. E-pub 2012 Aug 8.

[9] A survey on Automatic Analysis of Statistical Properties of Rheumatoid Arthritis using Digital Image Processing Prof G.S. Mate1 , Dr. A. K. Kureshi2 , 30th July,2017

[10] H.-T. Lin and L. Li, "Reduction from cost-sensitive ordinal ranking to weighted binary classification," Neural Computation, vol. 24, no. 5, pp. 1329–1367, 2012.

[11] A survey on deep learning in medical image analysis Author links open overlay panel GeertLitjensThijsKooiBabak Ehteshami Bejnordi LaakBramvan GinnekenClara I.Sánchez,Received 27 February 2017, Revised 24 July 2017, Accepted 25 July 2017, Available online 26 July 2017.

[12] Automatic bone boundary detection in hand radiographs by using modified level set method and diffusion filter. Garcia In IEEE 6th International Workshop on Computational Intelligence and Applications, Hiroshima, Japan, July 13, 2013.