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Methods to Diagnose Melanoma: A Survey.

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ABSTRACT

In this paper we have analyzed the different ways to diagnose melanoma. Melanoma is a cancer that occurs in a certain type of skin cell. It is considered as the deadliest and most aggressive form of skin cancer which leads even to death. So, it is necessary to find the ways by which can be diagnosed. So we have made survey on various types of skin cancer, its classification and found the various ways by which it can be diagnosed.

Keywords: Malignant melanoma, segmentation, nevoscope, ABCDE

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INTRODUCTION

When the normal structure and function of the skin is studied it will be easy to understand melanoma. Skin is the largest organ in our body and it protects the internal organs from injury since it covers the internal organs. Skin also prevents loss of too much of water and other fluids from our body them from injury. It helps to control our body temperature and as a barrier to germs. It helps the body to make vitamin D and it protects the rest of the body from ultraviolet (UV) rays.

The epidermis, the dermis , and the subcutis are the three layers of the skin are. Epidermis is the top layer of skin which is very thin averaging only about 1/100 of an inch thick. It protects the deeper layers of skin and the organs of the body from the environment.

The main types of cells in the epidermis include main types of cells which are

Squamous cells: are flat cells in the outer part of the epidermis.

Basal cells: These cells are in the lower part of the epidermis, called the basal cell layer. To replace squamous cells that wear off the skin's surface Basal cells constantly divide to form new cells. As these cells move up in the epidermis, they get flatter, eventually becoming squamous cells.

Melanocytes: These are the cells that can become melanoma. They make a brown pigment called melanin, which gives the skin its tan or brown color. Melanin protects the deeper layers of the skin from some of the harmful effects of the sun. For most people, when skin is exposed to the sun, melanocytes make more of the pigment, causing the skin to tan or darken. The epidermis is separated from the deeper layers of skin by the basement membrane. When a skin cancer becomes more advanced, it generally grows through this barrier and into the deeper layers.

Dermis: Dermis is the middle layer of the skin which is much thicker than the epidermis. It contains parts such as hair follicles, sweat glands, blood vessels, and nerves that are held in place by a protein called collagen. Collagen is the one which gives the skin its elasticity and strength.

Subcutis: Subcuits is the deepest layer of the skin and the lowest part of the dermis which form a network of collagen and fat cells. To protect the body's organs from injury the subcutis conserve heat and act as a shock-absorber.

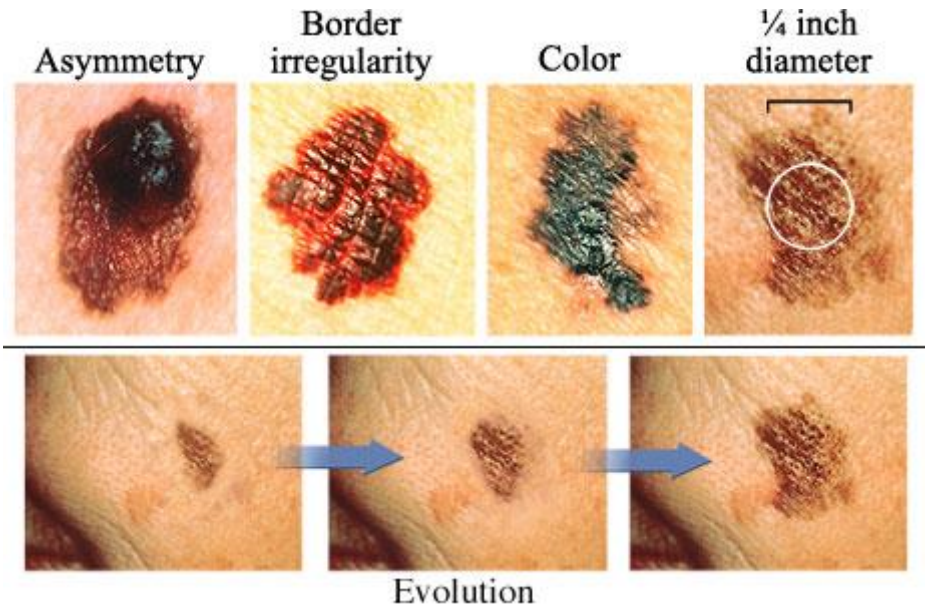

Figure 1: ABCDEs of Melanoma Skin Cancer

This is the Sample picture which depicts the ABCDEs of melanoma skin cancer. The meaning for ABCDE is given as, Asymmetry is that, from figure One half doesn't match the appearance of the other half. Border irregularity is that the edges are ragged, notched, or blurred. Color. (Pigmentation) is not uniform. Shades of tan, brown, and black are present. Dashes of red, white, and blue add to a mottled appearance. Diameter is that the size of the mole is greater than 1/4 inch (6 mm), about the size of a pencil eraser. Any growth of a mole should be evaluated. Evolution is that there is a change in the size, shape, symptoms (such as itching or tenderness), surface (especially bleeding), or color of a mole [1].

METHODS TO DIAGNOSE MELANOMA

The crucial parameters such as shape, color and size of the lesion can be found by Multispectral optical transillumination (MST) imaging of skin lesions non-invasively. To illuminate the lesion a 300 W halogen light source is used. Light is directed into the skin by A fiber optic cable is used to to illuminate the skin through a ring light guide [2]. The light which is remitted from skin passes through short pass filter (to remove long red and IR) and a 520, 580, or 610 nm narrow bandpass filter (±l0nrn) to select a specific spectral band. The nevoscope images are collected by using a AGFA ephoto 1280 high resolution digital camera. The MST images of raised skin lesions are collected and displayed in grey scale with different wavelength. The wavelengths are namely with (a) white light (b) a 520 nm bandpass, (c) a 580 nm bandpass, and (d) a 610 nm bandpass filter.

Since the skin is elastic in nature.The penetration depth within the skin is wavelength specific light entering the skin and remitting from the skin is nearly at same wavelength. The two dimensional information from the MST images about the skin lesion are collected whose depth belongs to penetration depth of light. At very low wavelengths melanin is a major absorber of light. The deeper layers of the skin is protected by pigment called Melanin which further protects the skin from some of the harmful effects of the sun . With increasing wavelength the obsorption of light by melanin pigment decreases[2]. When wide band white light is passed through raised part of skin a nonlinear composite of remittance collected over all wave-lengths is observed. Absorption by melanin at 520 nm (blue) wavelength provides surface information from the upper layers of the lesion only. Absorption by melanin at 580nm green light is absorbed less and thus penetrates deeper into the lesion providing features associated with the upper epidermal region. The image collected with red light (610nm) shows structural information at lower levels of the epidermis. Red light has relatively deep penetration in pigmented lesions, showing significant image contrast throughout. However, due to its lower absorption by melanin, red light does not resolve lesion boundaries well in thin layers of pigmentation. The combined analysis of the MST images can give information regarding the cell growth pattern within the lesion. In a clinical setting, regular non-invasive. In the early diagnosis process and classification of melanoma, MST examination of a patient's skin lesions over time with subsequent analysis of archived images has great potential [2].

There, that is, The abnormal melanin distribution in dermis layer and a peripheral blood net are two significant signs indicating malignancy of a melanoma. To diagnosing malignant melanoma non-invasively a multi-spectral optical Nevoscope is developed here. To reconstruct the melanoma in terms of Nevoscope geometry an algorithm is proposed. At 580nm and 800 the algorithm has been verified on an optical tumor model [2]. To investigate malignant melanoma the reconstructed melanoma is consistent with the tumor model which suggests a great potential of using Nevoscope.

The proposed algorithm is verified for the Nevoscope with a 1.2cm diameter. With equivalent width its 1.2cm diameter detector plane is divided into 20 rings. Each ring is further broken into a number of detectors and all detectors maintain the same size. When their values are interpolated from trans-illumination image this method will avoid error. In addition, for each ring only photon histories of one detector need to be recorded when the Jocobian matrix is evaluated. By rotating the recorded ones photon histories of other detectors at the same ring can be obtained. Using MC simulation on normal skin model and the tumor model two images are generated [2].

DeOxy-hemoglobin and Oxy-hemoglobin have identical absorption coefficients at 580nm and 800 nm [3]. So we don't need to consider oxygen saturation of blood for the reconstructed images. At 580nm and 800nm the results have been re-scaled in terms of their maximum reconstructed values. Thus the brighter regions correspond to higher absorption coefficients. In both results, the layer which contains melanin has high absorption. Additionally, high absorption is presented in layer at 580nm while there is only low

absorption in the same layer at 800nm. It means layer at 580 nm must contain a blood net according to the absorption spectrum of blood. The results are consistent with the optical tumor model which suggests that multi-spectral optical Nevoscope has a great potential to be utilized to characterize malignant melanoma. The final objective of this study is to present spatial distributions of melanin and blood through multi-spectral measurement. To achieve this, two problems would be addressed in our future study. First of all, the quality of reconstruction may be improved with optimally selected wavelengths. Sachin [4] has illustrated a linear correlation analysis to select wavelengths for Nevoscope. We are going to extend it to near-infrared spectra. In addition, as indicated by Color [5]. Wavelengths used in optical imaging also affect separation of choromophores. This will also be taken into our consideration. Secondly, it is well known that inverse problem of optical tomography is a typical underdetermined one. Out of many possible solutions, the expected one should meet some prior hypothesis such as smoothness [6] or be constrained by prior information [7].

Another method to diagnose early recognition of malignant melanoma has been developed where images from Epiluminescence microscope is obtained .From this computerized analysis of images are obtained. By applying several basic segmentation algorithm and fusion strategy binary mask of skin lesion is determined. By statistical feature subset selection method significant feature are selected. The final result gives a sensitivity of 87% with specificity of 92% [8].

Another method to classify pigmented skin lesion image is by natural induction method. This method, which is considered as non-invasive approach can be used to detect melanoma in early step. Here wavelet and attribution calculus is used to diagnose melanoma dermatologically. Here AQ21 application is used to discover the pattern in the skin images. Also, the performance of present approach when compared to other machine learning method which is tested on same data set and analysis is very high [9].

In this method, first a photograph has been taken of the lesion and the image is preprocessed to extract the region of interest. On applying Bayesian rules and in neural network several characteristics of image characteristics are analyzed. At last, final decision is extracted from the individual decision of each method. Here, for the diagnosis of melanoma three phases are designed. First they are preprocessed which includes segmentation, second selection of characteristic is done, third classification is performed. By changing the number of neuron in the hidden layer a final combination combined classification. All these values gives a value of confidence for each classifier. In this method the classification rate is 92% good and the percentage of sensitivity is 78% [10].

Early detection of melanoma is one of the greatest challenges of dermatologic practice today. A new diagnostic method, the “ELM 7 point checklist”, defines a set of seven features, based on colour and texture parameters, which describe the malignancy of a lesion. It has been presented as faster and with the same accuracy than the traditional ABCD criteria in the diagnosis of melanoma. In this paper a new system for automated diagnosis of melanocytic skin lesions, based on ELM 7 point checklist, is introduced[11] In the paper an automatic measurement system for the diagnosis of melanoma based on 7-points check list applied on epiluminescence microscopy (ELM) skin lesion images is proposed. The achieved performances are very promising and the whole diagnostic system will be used for both screening campaign and followup of suspicious lesions. Future work will be focused to i) develop suitable algorithms for the detection of the Atypical Vascular Pattern and Irregular Dots/Globules and ii) include into the system software a quantitative estimation for the reliability concerned with single parameter detection and the lesion diagnosis [12].

Here subset of genes are selected which contains candidate genetic biomarkers. The derived gene signature is then utilized in order to select imaging features derived gene signature is then used, which characterize disease at a macroscopic level. Using information gain ratio measurements and looking at gene ontology tree, a set of 32 uncorrelated genes were identified the molecular regulation of melanoma, these expression across samples correlates highly with the different pathological condition. The classifiers are trained with these selected genes and imaging features that could generalize well when discriminating melanoma samples.

Thus, in this paper integrated dataset is used which related to cutaneous melanoma that combines two separate sets is providing complementary information. Here a subset of genes that comprise candidate genetic biometric are selected. From the gene signature, imaging feature is extracted, which identifies the disease even at macroscopic level [13].

In this paper for border segmentation of clinical skin lesion images, interactive object recognition methodology is used. This proposed cascade classifier gives a sensitivity of 83.06% and specificity of 90.05%.To differentiate melanoma from non-melanoma lesion preprocessing, feature extraction, design and evaluation are performed. Here cascade classifier is used which gives 90.05% of sensitivity [14].

In this proposed method the images are captured via smart phone whose detection runs on Smartphone completely. These images which are captured by smart phone which are loosely controlled are subjected to memory and computation constraint. Here automatic feature extraction methods are used where fast detection and fusion of two fast segmentation results are combined. Then new feature is proposed to capture the color variation and border irregularity. The automatic feature extraction helps in finding more efficient feature [15].

CONCLUSION

In this paper various methods for the early diagnosis of malignant melanoma has been analysed. The survey from various papers has taken and the methods to diagnose the early stage of melanoma have been consolidated. The shape, color and size of the lesion can be found by Multispectral optical transillumination (MST) imaging of skin lesions. With various wavelengths the characteristics of the absorbent capability of melanin has been analyzed. By applying several basic segmentation algorithm and fusion strategy binary mask of skin lesion is determined which also helps in early detection of melanoma. The natural induction method which is considered the as non-invasive approach which can be used to detect melanoma in early step.

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REFERENCES

[1] http://www.webmd.com/melanoma-skin-cancer/abcds-of-melanoma-skin-cancerSource: NCI Visuals Online. Skin Cancer Foundation. http://visualsonline.cancer.gov/about.cfm.

[2] Ananda Kumar, Atam P. Dhawan Patricia Rehe, Prabir K. Chaudhuri. Multi-Spectral Optical Imaging of Skin to Diagnose Malignant Melanoma, Proceedings of The Rrsl Joint BMEEMBS Conference Serving Humanity, Advancing Technology Oct13-16, 1999; pp. 1098.

[3] Song Wang BS, Atam P Dhawan. Non-invasive Diagnosing Malignant Melanoma by Multi-spectral, Proceedings of the 28th IEEE EMBS Annual International Conference Optical Nevoscope, 2006; pp.3636-3639.

[4] Sachin V Patwardhan, Atam P Dhawan and Patricia A Relue, “Wavelength selection for multi-spectral imaging of skin lesions using Nevoscope ”, Proc. IEEE 29th Annual Northeast Bioengineering Conference, 2003;pp.327-328.

[5] Alper Corlu etc. Appl Opt 2005;44(11).

[6] Wenwu Zhu, Yao Wang, Nikolas P. Galatsanos, and Jun Zhang. IEEE Trans on Medical Imaging. 1999;8(11).

[7] Ang Li etc. Appl Opt 2005;44(10).

[8] Harald Ganster, Axel Pinz, Reinhard Röhrer, Ernst Wildling,Michael Binder, and Harald Kittler Automated Melanoma Recognition. IEEE Trans on Medical Imaging 2001;20(3):233-239.

[9] Grzegorz Surówka. Inductive Learning of Skin Lesion Images for Early Diagnosis of Melanoma, International Joint Conference on Neural Networks, 2008;pp.2623-2627.

[10] Ruiz D, Member, VJ Berenguer, A Soriano, J Martin. A cooperative approach for the diagnosis of the melanoma, 30th Annual International IEEE EMBS Conference Vancouver, British Columbia, Canada, August 20-24, 2008;pp.5144-5147.

[11] Margarida Silveira, Jacinto C. Nascimento, Jorge S. Marques,André R. S. MarçalTeresa Mendonça, Syogo Yamauchi, Junji Maeda, Jorge Rozeira, IEEE J Selected Topics In Signal Proc 2009;3(1):35-45,.

[12] Di Leo G, Paolillo A, Sommella P. Automatic Diagnosis of Melanoma: a Software System based on the 7-Point Check-List, Proceedings of the 43rd Hawaii International Conference on System Sciences 2010;pp.1-10.

[13] Ioannis Valavanis, Ilias Maglogiannis, Aristotelis A. Chatziioannou. IEEE J Biomed Health Informatics 2015;19(1):190-198.
[14] Sabouri P, GholamHosseini H, Larsson T and Collins J. Conf Proc IEEE Eng Med Biol Soc 2014;6748-6751.
[15] Thanh-Toan Do, Yiren Zhou, Haitian Zheng, Ngai-Man Cheung, Dawn Koh. Conf Proc IEEE Eng Med Biol Soc 2014;6752-6757.