A STUDY OF RECENT EARLY DETECTION MODELS OF MELANOMA IMAGES AND PROCEDURE FOR PRECLUSION

¹ Tammineni Sreelatha, Research Scholar, Department of Electronics and Communication Engineering, Jawaharlal Nehru Technological University Ananthapuramu, Ananthapuramu, AP, India Corresponding author E-mail: tamminenisreelatha7@gmail.com

² Dr. M.V. Subramanyam, Professor & Principal, Department of Electronics and Communication Engineering, Santhiram Engineering College, Nandyal, AP, India E-mail: mvs.santhiram@gmail.com

³ Dr. M.N. Giri Prasad, Professor, Department of Electronics and Communication Engineering, Jawaharlal Nehru Technological University Ananthapuramu, Ananthapuramu, AP, India

E-mail: mngiriprasad9@gmail.com

Abstract:

Skin cancer is mainly due to exposure of skin towards UV radiation. Due to which DNA damage will occur and skin cells will multiply which forms malignant tumors, due to this the risk will increase. Out of various types of skin cancers, Melanoma is very dangerous if is not identified & treated in initial stage. Therefore, it is obligatory to work on efficient initial identification methods of suspected lesion for the determination of melanoma type in the initial stage and to reduce the drawbacks present in the existing state-of-arttechniques. Automatic diagnosis of skin lesions within dermoscopy images is a crucial step toward developing a decision support approach for skin lesions early detection. This process includes segmentation of the lesions, extraction of the features and classification. Before the segmentation of an image, it is mandatory to go through pre-processing and Noise elimination. Still, Lesion segmentation can be challenging, as these skin images have various artifacts distorting the uniformity of the lesion area. In case of border of the lesion is blurred and if the distinction over the suspected lesions and its neighbouring part is very less, some of the segmentation methods have difficulties in the detection process. Along with lesion segmentation, feature extraction & classification are essential steps in this recognition process. Usually, the proposed models can be tested by using PH2 dermoscopy image data records. In this paper, by keeping all these things in view, we presented various recent early detection and prevention models of skin cancer that can be used for diagnosis along with advantages and disadvantages of each method. And finally the research gap is presented along with problem identification.

Keywords: Melanoma, Lesions, Segmentation, Feature extraction, Early recognition

I. Introduction:

Melanoma is very dangerous type skin cancer and more than 70 percent of death due to skin cancer will occur due to this. [17] Melanomas develop from malignant melanocytes. The gross majority of melanomas occur in the skin, the so-called cutaneous melanomas (CM).

Among Caucasian populations in Northern and Western Europe, melanoma incidence rates are increasing steadily by at least three percent each year. [16]

As mentioned earlier, melanoma mortality rates are stable or decreasing, while melanoma incidence rates are increasing. Since, additionally, melanoma is usually diagnosed in patients of a relatively young age [18-20], overall, the total number of patients suffering from melanoma is accumulating. Consequently, the total burden of melanoma is assumed to be increasing among Caucasian populations. As the overall burden of melanoma is increasing; prognosis strongly depends on the stage at diagnosis; and, most importantly, effective treatments for advanced stages are lacking, there is a high potential benefit for the prevention of melanoma. Only sun burns and sun exposure are, at least in theory, amenable. Indeed, sun protection measures are part of melanoma prevention programs. In some high risk countries, such as Australia, comprehensive sun protection programs have been implemented over a decade ago and sun screen use is widely promoted to the general public. These public health campaigns have increased awareness on skin cancer and the adverse events of excessive sun exposure, but failed to change the sun exposure behavior

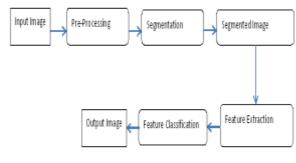


Figure 1

in the general population. Lack of behavioral changes and possibly also the lack of awareness is the main reason behind Melanoma [14]. Therefore, alternative approaches in melanoma prevention, such as chemoprevention, should be considered for high risk populations.

The general objectives of any skin cancer detection is to extract efficient lesion shapes and reliable identification of the lesion borders, to evaluate a precise pre-processing technique to segment skin melanoma efficiently, to evaluate different efficient features such as colour, texture, shape, low-level contrast features using the proposed skin lesion segmentation technique, to minimize the drawbacks of existing state-of-art-techniques using the proposed noise elimination techniques, to conclude superiority of the model using different datasets, experimental result need compared with various conventional methodologies over the parameters like accuracy, sensitivity and error.

The general procedure of lesion processing is shown in figure 1. Segmentation is a procedure which subdivides an image into its element regions. The purpose of the segmentation part is to make plainer or modify the characterization of considered lesion into entity which is easy to illustrate and expressive. Lesion can be generally used to detect objects and borderline in images. There are many models in segmentation so the subclass is carried based on the issue being solved. Once the segmented image is ready, the next work is extracting the features followed by classification to get the final output image or results. The performance of the proposed models can be measured by using the parameters like Accuracy, sensitivity and specificity. The above mentioned parameters can be calculated by using following equations 1,2 and 3 which depends on the values of count of true positive pixels(TP), count of false positive pixels(FP), count of true negative pixels (TN) and count of false negative pixels(FN).

| [TP + TN] | |
|--|---|
| $Accuracy = \frac{1}{[TP + FP + TN + FN]}$ | 1 |
| $Sensitivity = \frac{[TP]}{[TP + FN]}$ | 2 |
| $Specificity = \frac{[TN]}{[FP + TN]}$ | 3 |

In this paper is different sections are as follows. In section II, we have presented a study on various available models. Section III presents the research gap observed with problem identified. Section IV presents the comparison analysis. Section V presents the conclusion.

II. Literature Survey:

Binu Sathiya et al. [1] presented various available techniques in the process of early recognition. And a comparison table shows the different methodology used in the respective paper along with the advantage of the methodology. From the analysis, it can be observed that by using k-means clustering algorithm, the detection procedure on histopathologic images gives better results and it produces an accuracy of 96.32%. And by using modified k-means algorithm, sensitivity will be more than 97% and specificity will be more than 93%.

Adheena santhy et al. [2] presented the basics on early recognition process using image processing and good comparison among different segmentation methods. Since, screening method with dermatologists is costly; an automated segmentation models discussed here for melanoma detection so that it is possible to reduce the no. of melanoma deaths if it is recognised in advance. A crucial move in melanoma detection is the procedure of doing segmentation. This detects the skin lesions border to distinguish the area of interest from framework skin image for next level which is feature extraction. In this paper, the different segmentation methods which are taken into consideration for the study are compared based on 3 parameters. Those are Accuracy, sensitivity specificity. The calculation of these above mentioned parameters depends on the values of TP, FP, TN and FN. Various segmentation methods compared are SRM, Iterative stochastic, Multilevel thresholding, adaptive thresholding, color enhancement & iterative segmentation. From the methods, it is understood that the maximum accuracy of 96.8% is possible with multilevel thresholding method, which is designed based on the Otsu principle in thresholding. The maximum sensitivity of 99.9% is possible with iterative stochastic model. The maximum specificity of 95.2% is possible with multilevel thresholding method. From this study, it is clear that multilevel thresholding method is showing best performance among various segmentation methods mentioned above.

Suganya et al. [3] presented the model for melanocytic and non-melanocytic images. As a part of detection procedure, in the first step the segmentation is performed using k-means clustering algorithm. And in the next step, the features like color, text and shape were extracted. And finally the classification is performed using SVM classifier. In the pre-processing part, the task of hair removal is major one. For thin hair, Dull razor software is used. Median filter process is used for smoothening when the lesion is having thick hair. CLAHE method is adapted here to get rid of non-uniform illumination. The feature selection is based on wilkis lambda model followed by

SVM classification method. The lesion data is used from Dermweb. Here for the evaluation, 100 images were taken from non-melanocytic category and 220 images were taken from melanocytic to check the final result. Epidermic layer of the skin is considered here for the classification procedure. The results are proved based on parameters like Accuracy, sensitivity and specificity. The calculation of these above mentioned parameters depends on the values of TP, FP, TN and FN. The presented model achieved 95.4% sensitivity, 89.3% specificity and 96.8% accuracy.

Farzam kharaji Nezhadian at al. [4] presented a new model with better results. Initially, active contour method is used for the segmentation of the lesions followed by extraction of texture and color features. The extracted features individually evaluated using SVM classifiers. And later texture and color features evaluated at a time, through which the efficiency of the system is concluded. When texture and color features were considered at a time, the proposed system has produced an accuracy of 97%, specificity of 97% and sensitivity of 96%. The accuracy comparison among various available methods and for different class of lesion type is compared in a table. ISIC skin images dataset is used in this paper to check the advantage of presented method.

Reshma M et al.[5] presented two different models for the recognition of melanoma. In the first model, a value called TDS is calculated with the help of features like ABCD. When the TDS result is below 1, it means that the considered lesion is not having melanoma. When the TDS value is more than 1 and less than 4.75, it means that it is possible to cure through early diagnosis procedure. When the TDS value is more than 4.75 and less than 5.45, it is not in a position to do diagnosis. Different classifiers are used to investigate the efficiency of the model. And it is concluded that the better efficiency with reduced complexity is possible through ANN classifier. And the through the second model, it is possible to recognise the type of skin cancer for the lesion.

Maen Takruri at al. [6] proposed that the Bayesian Decision Fusion with multiple of classifier can be used for the better recognition rate of the melanoma. To prove that the proposed model achieves higher result, the results are compared with existing decision fusion models for the parameters like accuracy as well as confidence score. For the lesion classification process, 3 different classifier models are designed which uses SVM classifiers.

S.A.R Naqvi et al. [7] proposed an efficient skin cancer recognition model which uses principle of

electromagnetics. In the proposed algorithm, the natural selections procedure is performed through the selection of better characteristics from each of the parent. The result of the cost functions is 0.0054.

Amulya P M et al. [8] presented an investigation on different available methods for recognition of skin cancer in advance. Here various approaches were investigated to recognise and to classify the melanoma. From the study of ABCD rule based classify model, it is found that there is a need of efficient features extraction and classify models. And it is also shown that, Compared to K-means and decision tree classification models, SVM classification model produces maximum accuracy. And the neural network based classifiers were produced better results than any other models, but the drawback is it consumes more time in training of the system.

Zhen Yu et al. [9] proposed a new strategy for lesion detection using deep learning and local descriptor encoding procedure. This presented model is efficient enough to generate various feature values to work among high amount of variation of lesions. Here for the evaluation of the proposed model, freely existing ISBI 2016 dataset has been utilized.

Prachya Bumrungkun et al. [10] presented that mostly general reason for death in Thailand includes colon cancer, lung cancer, breast cancer, cervical cancer, etc. The skin cancer is one among the different cancer types, in which the count increases every year. As a usual process, initially in the segmentation procedure, SVM and snake contour models were proposed. However, it is concluded that some other deep classification procedures may be necessary for improving the results of the segmentation.

Tammineni Sreelatha et al. [11] proposed an efficient GFAC strategy which produces segmented image. In this paper, the image segmentation technique is introduced along with pre-processing and noise removal to reduce the noise and to make fast execution. A comparison study of different algorithms is presented in consideration of 3 parameters, which are accuracy, Disc similarity coefficient and specificity. It can be observed that the proposed method produced an accuracy of 98.64%, specificity of 99.22% and DSC of 97.08%. The efficiency of the proposed method is evaluated by using PH2 dataset.

Charles M.Balch et al. [12], presented that Melanoma staging is performed according the validated and internationally standardized Melanoma staging System of the American Joint Committee on Cancer (AJCC). Tumor thickness, also referred to as Breslow's thickness is one of

the strongest prognostic factors and is measured from the skin surface. Other factors that predict poor prognosis include advanced age at diagnosis, male gender, ulceration, race, anatomic site (trunk, head-neck region, extremities), and certain histogenetic subtypes, such as acral melanoma. The histopathological subtypes are classified according to the World Health Organization Classification of Tumours. [13].

III. Research Gap:

Literature presented proves that the significance and complexities in designing a real time model contains preprocessing and efficient features like texture, color shape and low-level features etc. In various literatures different skin lesion segmentation models Support Vector Machine (SVM) [10], deep residual neural network (ResNet) [9], Bayesian Decision Fusion [6], Texture-based [4] and Computer-Aided Diagnosis [3] are adopted to counter the challenges of diagnosis of skin lesion segmentation in Melanoma. Accurate segmentation in melanoma is an

important and complex task. If the image border is contains blur and if the variation over the affected area and its surrounding area is very less, some of the segmentation methods have difficulties in the detection process. To the best of our knowledge very few techniques till date that are able to provide efficient automated skin lesion segmentation using texture, colour shape and low-level features for melanoma images which is used to provide effectiveness, efficiency, as well as the generalization capability with minimum delay.

The main problem that is the peoples are not aware of several things which affects their skin care. Diagnosis by doctors is dependable, but the problem is it time consuming with more complexity. If the procedure works on automatic diagnosis, doctors can save large amount of time and it helps for more accurate diagnosis. From the investigations, we can observe that it is curable more than 90% if diagnosed early; curable is less than 50% if it the diagnosis is late.

IV. Comparison Table:

| Refere | Name of the | Publishe | Pre . | Segmentation | Feature | Classification | Remarks |
|--------------|--------------------------|----------|---|---|--------------------------------------|-------------------|---|
| nce paper | Author | d year | processing | | Extraction | | |
| No. | | | | | | | |
| 2 | Adheena santhy et al. | 2015 | | Compared over: 1. SRM 2. Iterative stochastic 3. Adaptive thresholding 4. Color enhancement and iterative segmentation 5. Multi-level thresholding | | | Maximum accuracy of 96.8% and maximum specificity of 95.2% is achieved with multilevel thresholding method. |
| 3 | Suganya et al. | 2016 | For thin hair, Dull razor software is used. Median filter process is used for smoothening when the lesion is having thick hair. | k-means clustering algorithm | Color, text and shape were extracted | SVM classifier | This model achieved 95.4% sensitivity, 89.3% specificity and 96.8% accuracy. |

| 4 | Farzam kharaji Nezhadian at al. | 2017 | | active contour method | Texture and color features were extracted | SVM classifiers | This model achieved accuracy of 97%, specificity of 97% and sensitivity of 96%. |
|----|--|------|--|--|---|--|--|
| 5 | Reshma M et al. | 2017 | | | TDS is calculated with the help of ABCD features | Better efficiency with reduced complexity is possible through ANN classifier | Two different models proposed for the recognition of melanoma severity and type respectively. |
| 6 | Maen Takruri at al. | 2017 | Hair removal and backgroun d noise elimination is performed. | K-Means algorithm is used | Wavelet transform, curvelet transform and GLCM are used | SVM classifiers | The performance of the proposed is compared with other models. |
| 9 | Zhen Yu et al. | 2018 | | Deep learning and local descriptor encoding procedure were used. | | | This presented model is efficient enough to generate various feature values to work among high amount of variation of lesions. |
| 10 | Prachya Bumrungkun et al. | 2018 | | In the segmentation procedure, SVM and snake contour models were proposed. | | | Some other deep classification procedures may be necessary for improving the results of the segmentation. |
| 11 | Tammineni Sreelatha et al. | 2019 | Pre- processing and noise removal to reduce the noise and to make fast execution | Proposed GFAC strategy which produces segmented image. | | | The proposed method produced an accuracy of 98.64%, specificity of 99.22% and DSC of 97.08%. |

V. Conclusion:

Different effective mathematical modelling techniques were discussed to identify the existing methods draw backs clearly. The performance of various discussed methods is evaluated by using various datasets. From literature, we can understand that different coefficients like Disc Similarity Coefficient, Accuracy, Specificity and

sensitivity are compared. In future, the plan is to work on various novel algorithms in segmentation, feature extraction and classification.

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