Malignant melanoma review: epidemiology and patient survival rate

Health & Medicine, Cancer

Malignant Melanoma is one of the most rapidly increasing cancers all over the world. In 2018 around 1, 78, 560 melanoma skin cancers were found in the United States of America and the rate is increasing ever since. Melanoma has been cured completely if it is detected at the early stage. Several automated methods have been used for analyzing the melanoma at the early stage which can increase the survival rate of the affected people for more than 5 years. Dermoscopy is an in vivo non-invasive imaging tool that aid dermatologists to examine the morphological features of melanoma efficiently. In this survey paper, we review the state of art methods and current technologies for skin cancer detection. Statistics and results from the most important implementations has been analyzed and reported. With the aim of improving the existing methods and to develop new techniques, this survey paper makes the contribution in different stages of computer-aided skin diagnosis system.

Malignant melanoma is a form of skin cancer type and it is considered most deadly. According to WHO (World Health Organization) 132, 000 melanoma skin cancer occur globally each year. In the United States of America, One in every five people has skin cancer in their lifetime. It is estimated that a 10 percent decrease in the ozone layer will results in 4500 different types of skin cancer.

Charles et al [1] identifies the melanoma using four basic features namely: thickness of the tumor, spread to lymph nodes, spread to other parts of the body, and its ulceration. There are four main stages in Melanoma namely Stage I, II, III and IV. These stages can be described in Table-I. Melanoma has to be identified at the early stage particularly for two reasons: First, the melanoma diagnosis is majorly depending on the tumor thickness rate. If it is detected at the initial stage then the survival rate of the patient can be increased for more than 10 years. Second, the melanoma is localized to the skin in most of the cases and that can be identified by very simple examinations. If the melanoma gets spread then it is not easy to detect the lesion using simple experiments. Early signs of melanoma can be detected by using " ABCDE (Asymmetry Borders Color Diameter Evolving over Time)" strategy. Since this ABCDE strategy, cannot determine the complex melanomas. Radiation Therapy and Immunotherapy [2] were the most common methods used previously in the treatment of melanoma. It shows better results when both of these methods work separately. Combination of these methods will increase the therapeutic effects and adverse effects. Hence this clinical method has not been used further.

Stage Melanoma Tumor Thickness Survival Rate

- I T1a melanoma Less than or equal to 1mm 10-years
- II Ulcerated T1b melanomas 1. 01mm- 2. 00mm 10-years
- III Regional Metastatic Melanoma 2. 01mm-4. 00mm 5-years
- IV Distant Metastatic Melanoma Greater than 4. 00mm 1-year

Computer Aided Diagnosis (CAD) system helps the dermatologists to differentiate the melanomas from the other pigmented lesions. This system uses a three step approach for analyzing the dermoscopic images 1) Segmentation; 2) Feature Extraction and Feature Selection and 3) Lesion Classification.

This work reviews the different segmentation, feature extraction and classification techniques. The organization of this paper is as follows: Section-II discusses the Literature Review; Section-III discusses the datasets that has been used for segmentation and classification algorithms; Section-IV evaluates and analyses the different algorithm techniques and their results, and finally Section-V concludes with the discussion about state of art methods and highlighting their research gaps.

Color Segmentation

Yuskel et al [3] proposed a novel thresholding algorithm that segments the dermoscopic nevus image based on Type-2 Fuzzy Logic. In this method the nevus image is converted into gray scale image and the histogram value has to be computed based upon certain threshold value. Finally Fuzzy logic has been used to segment the color from the image. It fine tunes the performance compared to other state of the art methods and it accurately segments the nevus skin images. In case of certain artificial irregularities such as irregular borders this method provides inaccurate results and misleads the segmentation process.

Zhen et al [6] proposed an idea that segments the color from the dermoscopic image using deformable model. Initially the RGB color spaces have been identified from the image. Median filter has been applied on each RGB space in-order to smoothen the image. Level set function and Otsu method has been applied to compute the statistical values of each pixel based upon the region. Deformable method has been combined with the speed function and the stopping criterion. Finally, the lesions have been classified as malignant and benign. It achieves the overall best performance in classifying the lesion. This process is semi-automatic hence the initial curve has to be defined manually. This method does not suitable for irregular shapes.

Yuan et al [9] enhanced the color segmentation technique by using Convolutional and Deconvolutional Network. This technique segments the lesion using color spaces. It combines the Red, Green, and Blue (RGB) color spaces with Hue, Saturation and Value (HSV) color spaces in order to improve the segmentation performance. This model belongs to Fully Convoltuional Network (FCN) category. Initially, this method forms a 3*3 kernel architecture that maintains both convolutional and deconvolutional layers. Features have been extracted from these layers and loss function Jaccard distance has been applied to each pixel of the lesion. Dual threshold method is applied to generate binary tumor mask from the output of the loss function. Finally, morphological operations have been applied to classify the tumor lesions. Computation time is very less compared to the other methods and the accuracy is more accurate. This segmentation performance works poor for certain image acquisition conditions.

Region Segmentation

Wong et al [4] state that Iterative stochastic region merging is used to segment the macroscopic images corresponding to skin lesion region. This method will be summarized as follows: Initially, the macroscopic image has been segmented by using Likelihood function that uses both Maximum Posterior Probability and Bayes Theorem. Artifacts in the macroscopic image have been handled by using Markov Random Field (MRF). Stochastic region merging algorithm has been applied on the image. The proposed merging region formula is (1): α(R_a , R_b) = exp [- □(E[R_a]-E[R_b])□

2/(⋀▒□(R_a, R_b)□)] (1)

The extracted regions are inserted into the priority queue in ascending order and the stochastic algorithm has been iteratively repeated until there are no further changes in the merged regions or only two regions are remaining. Finally, the lesion region has been separated from the image. This method is robustness to all the image acquisition conditions such as noise, artifacts and color variations. Since this method does not suits for larger datasets. Hence it is computationally intensive. It selects only a limited set of features for segmentation. Boundary Segmentation

Peruch et al [5] proposed a new technique called MEDS segmentation which means Mimicking Expert Dermatologists Segmentation. This technique combines thresholding segmentation with number of optimizations. MEDS has been carried out in 5 different stages namely: Stage-I: Pre-Processing; this will remove the hair from the melanocytic lesions using virtual shave method. Stage-II PCA; Principal Component Analysis technique has been used to observe the statistical observations in multi dimensional space. Stage-III: Noise Reduction; the grayscale image that has been selected corresponding to the projection based on the first principal component analysis uses a filter that increases the segmentation accuracy. Stage-IV: Color clustering; it will cluster the lesions into normal skin lesion and melanocytic lesion. Generally, lesion regions are slightly darker than the melanocytic lesion. Stage-V: Post processing; finally the image undergoes down sampling to detect the boundaries of each lesion component and to classify the melanoma and non-melanoma lesion. This method provides accurate results as any segmentation techniques.

Ahn et al [7] proposed a method called saliency detection method that integrates with the Bayesian framework to delineate the shape and boundary of the lesion accurately. In this method, dermoscopic image undergoes hair removal process and then the boundary connectivity of an image region has been calculated by using this formula (2): $BC(A) = (|\{X \mid X \in A, X \in BndS\}|)/\sqrt{(|\{X \mid X \in A\}|)}$ (2)

X represent Image segment, BndS represents Boundary Segments that quantifies the extent that an area is connected to that image boundary. Sparse reconstruction error was used to measure the probability where the segment belongs. Finally, the segment that has larger reconstruction error against the background is considered to be malignant lesion. It is an optimization algorithm compared to other methods. This method does not suit for very small image and the image located at the boundary. Bozorgtabar et al [12], Jafari et al [14] enhanced the boundary and border segmentation technique using Deep Convolution Networks. First, the image has been segmented by using FCN based initial segmentation. It trains the entire image pixel by pixel mapping for semantic segmentation. This FCN method integrates Visual Geometry Group (VGG) that predicts the scores for background and boundary skin lesion. This output probability is given as an input to the Super pixel mapping. It uses Simple Linear Iterative Clustering (SLIC) technique to extract the super pixels from the image. Local and global features has also extracted from the image. Average prediction score has been calculated for each super pixel to predict the final classification. This method outperforms the fully convolution network. The energy function has not taken in consideration, since that makes the largest differences in segmentation masks.

Feature Segmentation

Gonzalez-Diaz et al [11] state a new method called " DermaKNet (Dermatologist Knowledge Network)" that segments the skin lesion using a set of pre-defined dermoscopic features that corresponds with the global and local structures of interest for dermatologists in their diagnosis. The pipeline for DermaKNet is as follows: Initially, the image undergoes Lesion Segmentation Network (LSN) that generates the binary tumor mask. Next, Data Augmentation Module (DAM) is used for generating additional view of the lesion by applying morphological operations. Dermoscopic Structure Segmentation Network (DSSN) is used to segment the skin lesion based upon eight set of dermoscopic features. This segmentation mapping is given as input to the Diagnosis Network (DN) that classifies the non-visual metadata and lesion. These non-visual metadata has been factorized further by using Soft max classifier to get the final predicted lesions.

Tajeddin et al [13], Sadri et al [8] proposed a new technique for feature extraction and selection in dermoscopic image. This method extracts the features such as color, shape, texture from all the normal lesion areas (general features) as well as the peripheral region of the lesion (local features). General features have been extracted from the image as an output of the segmentation step. A framework has been used for extracting the local features called Daugman’s rubber sheet model. Initially, morphological operations have been applied in the lesion mask to extract the image and the mask separately. Now the centre of the lesion alone is present and the distance function has been computed to determine the peripheral region or the region that is located close to the boundary. Then the rubber sheet model is used to transfer the radial structures into vertical representation and the streak like structures in lesion can also be determined easily. This model fine tunes the feature extraction process.

Lequan et al [10] proposed an idea that recognizes the melanoma automatically by using Fully Convolution Residual Network (FCRN). This method integrates both segmentation and classification techniques. The segmented image alone produces the exact lesion size. Hence the segmented image is given as input to the classifier. A 7*7 network pool average layer has been constructed to extract the global deep residual features. Soft max and SVM classifier has been used to predict the malignant lesion. This method ranks first in classification rather than segmentation. Classification time is very less compared to previous methods.

Sabbaghi et al [15] represents a Quad Tree technique that detects and classifies the melanoma using color detection. Otsu thresholding method has been applied on the image to get an optimized color channels. Color palette has been constructed with the help of dermatologists that has been used for the identification of the color in the melanoma. Each pixel in the image has been clustered using Quad tree clustering in order to reduce the computational complexity. This cluster image is converted into a single RGB image and the color labeling decides the amount of lesion present in the skin. Melanoma classifier based upon color detection is a complex problem. Hence different classifiers have been chosen such as Kernel Support Vector Machines (SVM), back propagation neural network, Linear Discriminant Analysis, and Random Forest. These classifiers achieve higher results than other state of art methods.

Four different segmentation methods were evaluated, as discussed in the above section. This evaluation was based upon certain measures such as Accuracy, Specificity, and Sensitivity. Hence, the performance of the different segmentation methods has been summarized in the Table-II. According to this survey, Thresholding segmentation is the best method compared to all other state of the art methods. Color, region, boundary and certain features are acts as a distinguishing feature for classify the benign and malignant lesion. Peripheral Lesion information outperforms well in the feature extraction compared with other methods. Different classifiers such as SVM, ANN, Random Forest, Back Propagation and Feed forward algorithms were used frequently for classifying the malignant lesions. More accurate results were obtained when these classifiers are implemented in the classification step.

Several dataset has been used for the automatic skin lesion segmentation. In these some of the datasets were publicly available. The details of those dataset were as follows: □PH□2 Dataset: □PH□ dataset has been developed in order to facilitate the segmentation and classification algorithms for dermoscopic images. This dataset contains 200 images in that 40 images are melanomas, 80 images are common nevus, and remaining 80 images are common nevus. ISIC Dataset: The International Skin Imaging Collaboration (ISIC) is an international effort to reduce the melanoma cancer all over the world. This dataset contains over 10, 000 images that includes benign as well as melanoma images.

In this survey, different techniques has been discussed for detecting the malignant lesion from the dermoscopy image at the earlier stage in order to increase the mortality rate of the patients. We review the state of art techniques in clinical practices as well as the CAD system and recent trends that have been developed in the field of malignant lesion detection. These systems states different stages such as segmentation, feature extraction and classification by using the extracted features. Different metrics has been used for evaluating each of the methods. The performance of the method has been interpreted under various imaging acquisition conditions.