Detection Of Melanoma Tumor in Dermoscopic Images Using Image Segmentation and Machine Learning

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Abstract. Skin cancer is considered one of the most dangerous and common types of cancer. Melanoma is a type of skin cancer caused by the abnormal growth of melanocytes. If the spread of melanocytes is limited to the subcutaneous layer of the skin, then it would be benign cancer. It can become deadly if the melanocytes introvert into the blood supply. The early detection of melanoma is crucial for effective treatment. Recently, implementing a machine learning algorithm on dermoscopic images has become a great tool for early detection. In this paper, we introduce an automated method for classifying melanoma from dermoscopy images into benign and malignant cancer using supervised learning methods. International Skin Imaging Collaboration (ISIC) and the Society for Imaging Informatics in Medicine (SIIM) image dataset were used for study. The images were normalized and then a hair removal algorithm was applied to eliminate occlusion caused by the patient's hair. Image segmentation using kmean clustering to extract the skin lesion /tumor from the background, followed by feature extraction based on the morphological structure, intensity, and texture features from the segmented data. After feature extraction, the data were used to train the classifiers and tested. Comparative analysis was also performed between different classifiers such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Linear Regression (LR), and K-nearest neighbor (KNN). To test the performance of the classifiers, we calculated the precision, accuracy, specificity, F1-score, confusion matrix, and ROC curves implemented. From the study, it was found that LDA and logistic regression were able to achieve an accuracy of approx. 93% and 92%. The proposed method can detect the presence of melanoma from dermoscopic images with good accuracy, which is comparable to deep learning-based and neural network methods.

Keywords: Melanoma Detection, Hair removal, supervised learning, Image segmentation, Image enhancement.

1 INTRODUCTION

Melanoma is caused by the uncontrolled production of skin cells known as melanocytes. Melanocytes are skin cells that contain color pigments known as melanin, which gives color to skin, hair, and eyes. The severity of melanoma depends upon the propagation of melanocytes. If the melanocytes penetrate the deeper layers of the skin and enter into the blood circulation, then it can become cancerous melanoma or malignant melanoma. Malignant melanoma is one of the deadliest types of skin cancer. According to the American Cancer Society in 2023 about 97,610 cases (58,120 cases in men and 39,490 cases in women) were diagnosed in the United States alone, while about 7,990 people (about 5,420 men and 2,570 women) are expected to lose their lives due to melanoma. According to the report, the survivability of melanoma patients greatly depends upon the early detection of cancer for effective treatment[1, 2][3].

The conventional method for early diagnosis of melanoma in clinical setup is dermoscopy, in which a dermatologist assesses the skin lesion by illuminating and magnifying the image of a region of the skin for increased clarity of the mole. This technique requires highly trained dermatologists to minimize false negative or positive diagnoses[4]. Because of this reasoning, diagnosing melanoma is a challenging task as there is no clear separation between benign and malignant melanoma using dermoscopy.

To overcome this limitation, this paper proposed an automated melanoma detection algorithm using imaging processing and machine learning techniques. The paper is structured as follows literature review, methodology, experimental results, and conclusion will be given about the presented work.

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2 LITERATURE REVIEW

This section provides a brief description of the related works that are implemented in the diagnosis of melanoma cancer. Melanoma may appear in different shapes, sizes, and colors, making it difficult to differentiate benign and malignant melanoma using conventional approaches. To overcome this, many research groups, implement a combination of image processing, machine learning, and deep learning techniques to automate the diagnosis process. Bethanney et al[5] performed a comparative study that classified melanoma using different supervised learning methods. The system segments the melanoma tissue by using adaptive thresholding. After segmentation, shape and texture features were extracted. For classification, the author implemented KNN, SVM, Decision Tree, MLP, and Random Forest. The result shows that the random forest has the highest accuracy (93%) compared to others. Viswanatha et al[6] showed CNN classifier is suitable for a classifier for this problem as compared to others. four-layer CNN model with a multiple-layer perceptron was able the classify the melanoma with an accuracy of 88.8% without using any image enhancement technique, which minimizes the computational cost. Shoail et al[7] implemented the ResNet50 CNN model to predict melanoma. ResNet50 is a pre-trained 50-layer CNN model, which is readily available online. The experimental result shows that the ResNet50 model was able to predict melanoma with an accuracy of 92.3%. A combination of deep learning and machine learning techniques has also been implemented to detect melanoma tissue. Codella et al[8] constructed a novel model to classify melanoma from dermoscopic images, by combining CNN and SVM models for image segmentation and classification. The CNN mode is used to detect the tumor characteristics such as tumor borders without applying any image processing technique or thresholding technique. Lastly, SVM is used to classify the feature as a benign and malignant tumor.

3 METHODOLOGY

The proposed method employs a supervised learning method to classify melanoma into benign and malignant lesions as shown in the figure. At first, the hair removal algorithm is applied to all the images in the dataset. The pre-processed data set was labeled and divided into groups of training, validation, and testing datasets. Afterward, an image segmentation algorithm is applied to the image to extract the tumor from the background. Thereafter, features such as shape, color, and texture were extracted, which were used to train the machine learning model. In this paper, SVM, Logistic Regression, KNN, Random Forest, and Decision Tree Classifiers were trained. Lastly, testing is then performed similarly, to check the efficiency of the system.

3.1 Dataset

The image data was gathered from the ***International Skin Imaging Collaboration (ISIC) and the Society for Imaging Informatics in Medicine (SIIM)***. The dataset contained a total of 33,126 dermoscopic training images of different skin cancers. Only 17,806 dermoscopic images were labeled [9].

3.2 Hair detection and removal

The presence of hair in the dermoscopy image makes it difficult to segment the tumor from the background image, reducing the accuracy or performance of the classifier. The original image is converted into YCBCR color format because the luminance (Y) component highlights the hair pixels more compared to the original image. To detect hair pixels a 5X 1 Kernel and bottom hat morphological operation is implemented on the Y component image, resulting in an output image that highlights only hair pixels. A binary image mask is created by applying normalization, and edge detection using adaptive thresholding. After the binarization operation, the hair pixels in the Y component images are replaced by implementing the region fill operation. The filling process replaces pixel values in the region with the adjacent pixel values that are nonhair pixels. Lastly, a median filter was applied to reduce edge artifacts.

3.3 Tumor Segmentation

A mean thresholding algorithm was implemented to segment tumor or skin lesion pixels from the skin pixels. To enhance the segmented image, opening, and erosion morphological operation was applied to remove any small patch having a radius of less than 5 pixels. Lastly, the fill operation was used to fill any holes in the segmented image

3.4 Feature extraction

From the segmented image morphological, color, and texture features were extracted. The details of the features are given in the following table.

Table 1. Details of the features extracted from the segmented image. Total of 18 features.

Features	Attributes	Methodology
Morphological	Tumor area, Tumor perimeter, Symmetry and Circularity	
Texture	Contrast, Correlation, Homogeneity, Energy, Entropy	Gray-level Co-occurrence Matrix (GLCM)[10]
Color	Mean, standard derivation, and Maximum value were calculated for Hue, Saturation, and value	Converting the segment image into HSV color format.

After feature extraction, a total of 7 classifiers were trained such as KNN, logistic regression, SVM (linear), SVM (cubic), Decision tree, and Random Forest. The training data set obtained after feature extraction was divided into the training dataset and validation data set (to reduce the overfitting problem). 75% and 25% of the feature dataset were used for training and cross-validation of the classifier respectively

4 Result

4.1 Evaluation of the image segmentation using the DICE similarity index

Figure 1 shows the results of the segmentation on selected images. The ground truth segmentation was constructed with the help of the dermatologist by manually drawing the ROI on the images. The ground truth masks are used as a reference for the evaluation of our technique. Our technique can segment the skin lesion properly if the original image does not contain any shadows or marks. These obstructions cause incorrect segmentation since they have a high pixel value and are detected as part of the lesion segment instead of the skin background. Due to incorrect segmentation, the DSI is low when compared with the reference image

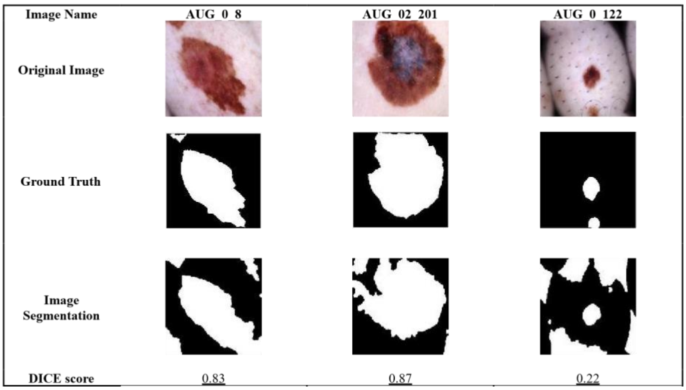

Fig. 1. Image segmentation validation using DICE similarity index score

4.2 Classifier's Performance Validation and Testing

Tables 2 and 3 show the validation and testing results of the classifiers. The test dataset consists of 3561 dermoscopic images, which was balanced having an equal number of images for melanoma and non-melanoma classes.

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Table 2. Validation results after training of classifier

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F1-score (%)
Decision tree	88.12	83.38	92.86	92.12	83.38	87.53
Random Forest	90.2	86.58	93.82	93.34	86.58	89.83
SVM (linear)	88.85	85.23	92.47	91.89	85.23	88.44
SVM (cubic)	92.02	87.93	96.12	95.78	87.93	91.67
KNN	89.13	88.32	89.94	89.78	88.32	89.05
Logistic Regression	92.69	87.48	97.92	97.68	87.48	92.30

Table 3. Testing result

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F1-score (%)
Decision tree	87.78	82.65	92.92	92.12	82.65	87.13
Random Forest	89.47	86.19	92.75	92.25	86.19	89.11
SVM (linear)	88.99	86.30	91.89	91.43	86.30	88.79
SVM (cubic)	92.22	87.82	96.63	96.31	87.82	91.86
KNN	89.30	88.21	90.39	90.18	88.21	89.18
Logistic Regression	92.47	87.54	97.42	97.13	87.54	92.08

5 CONCLUSION

In this paper, an automated melanoma detection algorithm is proposed, which can classify skin lesions into melanoma and non-melanoma using image processing and machine learning techniques. the classifiers were tested using the ISIC 2020 dataset. The accuracy of the logistics regression and SVM (cubic) was greater than 92%. Hence the overall algorithm can automate the diagnosis approach for accurate and consistent identification of skin tumors with exemplary capability for image-based treatment techniques

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