 ISSN 2579-7298

Melanoma Detection And Classification In Dermoscopic Images Using Resnet50 And Hair Removal Feature

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ARTICLE INFO

Article history
Received
Revised
Accepted

Keywords
Skin lesion analysis,
End-to-end multi-tasking framework,
Deep learning,
Melanoma segmentation,
Convolu- tional neural networks

ABSTRACT

Melanoma is the most common skin cancer, and it is increasing widely. Automatic skin lesion detection from dermoscopic images remains a challenging task. Many efforts have been dedicated to this challenge using various methods, but due to its poor robustness, it is not good for the analysis of melanoma skin lesions. Propose a method for skin lesion detection and classification tasks simultaneously to make sure feature learning is successful. The base of feature pyramid networks and region proposal networks is ResNet50, which is used here. The network learns features more quickly using a three-phase cooperative training technique. Before entering this model, the hairs from the images are removed.

1. Introduction

The most common type of cancer is skin cancer, and melanoma is becoming more prevalent worldwide. Early melanoma identification is crucial because it can improve treatment and boost survival rates. The most popular type of medical imaging is dermoscopy, which has an early detection rate for skin lesions. Aside from the presence of hair, veins, and borders, melanoma skin lesions in dermoscopic pictures have a discernible similarity to non-melanoma skin lesions. Its presence makes it more difficult to find melanoma from dermoscopic pictures.

Different approaches are being offered to deal with these problems. One is based on custom-built features used in traditional image processing and machine learning algorithms, and the next is based on techniques related to deep learning with the concept of convolutional neural networks (CNNs). To extract characteristics and integrate them for improved performance in the first kind, various feature selection techniques are presented; nevertheless, these algorithms have weak robustness. The deep learning method has been gaining more and more attention as a result of its capacity for autonomous feature extraction. The real dermoscopy Pictures serve as the input for the point-to-point deep learning multi-task system, which jointly generates results for melanoma classification and detection.

Early detection of melanoma is important for better treatment. The class imbalance problem affects the performance of the approaches, Malignant classes have far fewer training samples than the dominant classes, making it difficult for the network trained through cross-entropy loss to recognise them. An end-to-end deep learning multi-task system takes the original dermoscopy image as its input and jointly generates results for melanoma classification. detection, and segmentation.

- The class imbalance issue in dermoscopy images is fixed, and segmentation accuracy is improved by employing an effective loss function based on the focal loss and the Jaccard distance.

- The use of ResNet can classify and label the object. The hairs on the images are removed for an accurate result.

The skin cancer benign and malignant dataset is used to check the efficiency of this work.

Review Of Literature

Detecting the melanocytes in the epidermic area is an important step for identifying melanoma skin cancer. Keratinocytes are very similar to melanocytes, so their Detection is very difficult in epidemic areas. Histopathology pictures are verified by the pathologists, and then the judgement leads to inner and outer-observer variability. To overcome this, they introduced an automated computational machine for quantitative and qualitative measurements. Different segmentation methods are introduced to differentiate keratinocytes and melanocyte cells. Cheng Lu [1] suggests that the already available automated computing tool for quantitative and qualitative measurements cannot find the correct location of melanocytes. So he introduced the LRRS algorithm, which is proposed to find out the candidate nuclei regions from the mean-shift partitioned image. For quantitative analysis, an LDED is proposed to find the local features and identify the location of melanocytes. In this paper, they can identify the location of melanocytes with a sensitivity rate of 82% and a 70% positive prediction rate. But they cannot identify the architectural features.

Euijoon Ahn [2] says that previously, CNN was used for detecting melanoma. It is the best deep-learning technique and it can predict patterns in each pixel. But a successful learning-based algorithm like CNN needs a large number of parameters and a large number of labelled training pictures. To notice these limitations, use the region-based saliency-based skin lesion segmentation framework. It detects visually visible regions or objects in the images. As a preliminary step in the processing, hairs on the photos are first eliminated. Lee et al.'s technique was used to crop out visible hair from the photos. The final image is smoothed after the hair pixels are swapped out with the surrounding non-hair pixels. To divide the image into N segments, use the simple linear iterative clustering (SLIC) technique. Using the Euclidean distance between each pair of adjacent segments (X, Y), an undirected graph was created. The square root of the area was calculated to make the picture segment resolution invariant. The boundary connectivity of each image segment is then measured to build a background template. A segment is more likely to be labelled as a lesion if the reconstruction error against the background template is greater. The residual-based sparse representation of the background templates was used to calculate the sparse reconstruction error. By taking into account other neighbouring segments, a context-based error propagation technique can be used to smooth the sparse reconstruction errors. A Bayesian framework is then used to map the pixels after this. Based on the similarities and contrasts between the pixel backgrounds, a Bayesian framework may identify wound boundaries. The skin lesion is so small that it is detected as part of the normal background region; this is the limitation of this work.

The mortality rate for melanoma is considered the most serious type of skin cancer. The mortality rate all over the world is increasing compared to other types of cancer. Tra- ditional machine learning models use handpicked features or deep learning to identify melanoma. It is not accurate, and they only use the ABCD rule for detecting melanoma cells. Here, an improved K-means algorithm is used to extract the region of interest from the images. A trained CNN model [3] named Alexnet, is used for the automated classification of skin cancer and the initial diagnosis of skin cancer using computerised microscopy-based methods. First, dermoscopic images in medical images must undergo data preparation to get rid of the noise. If the noise is not removed, segmentation may be impacted, leading to erroneous detection results. After that, the region of interest is extracted from the photographs. Because the lesion locations on the pictures may be found via the ROI, it is more crucial to extract features from the lesion area than from the full image. For that, a modified K- mean algorithm is used. Depending on the intensity levels, it divides the images into non-overlapping clusters of pixels. If any pixel value or data point changes, all of the other pixels in the image will also change. The region of interest is located, and then the data augmentation is carried out. The number of inputs is increased using these data augmentations. Here, using a few processes using the original image as a starting point, they transform seven photographs in all. Cropping the original images from the right, left, and bottom sides, flipping, mirroring, and rotating at 270 degrees are the steps used for data augmentation. After the data augmentation, the images are sent for resizing based on the AlexNet requirements. When the image goes through AlexNet, it can be classified based on the features obtained.

Late detection of melanoma causes malignancies that affect other parts of the organs. Different computer vision techniques are used for analysing dermoscopic images, but the visual similarity between the affected region and the normal skin, hair, gel bubbles, and clinical marks gives less accurate results. Applying morphological operations to remove hairs, gel bubbles, and clinical marks from the dermoscopic images. Highly correlated and less correlated infected regions are detected using the YOLOv4 [4] object detector. This contains a three-step process: the skin refinement process, melanoma localization, and melanoma detection. Remove external noise such as air bubbles, hairs, wound marks such as clinical marks, and so on during the skin refinement step. The next step is to use YOLOv4 to locate the melanoma. It is capable of detecting multiple melanoma lesions present in a single image, as well as multiple types of skin disease, and reduces the need for a biopsy test for melanoma diagnosis. There are three networks in YOLOv4: the backbone network, the neck region, and the head region. The input images were processed through a convolutional backbone network to describe the high-level representation of melanoma. This type of high-level representation can aid in the detection of melanoma borders in images. Then multiple bounding boxes were created in the neck region. These bounding boxes can extract the features of the location accurately. Next is the head part of the YOLOv4. Here, it can find the location of the melanoma based on the features that are extracted from the other two networks. Using a snake model of active contour segmentation, the discovered lesion is subsequently processed to isolate the specific melanoma boundaries. This method detects melanoma and segments it effectively and precisely. Due to visual similarity, precise melanoma detection is challenging

2. Method

2.1 Dataset

The dataset for this model is benign vs. malignant skin cancer. Images of normal and malignant skin moles are evenly distributed in the dataset ”Skin cancer: malignant vs. benign.” The information comprises two folders that each include 1800 images (224*224) of the two different varieties of moles.

Fig. 1. Images from Benign class

These are the different images present in the dataset in two classes:

Fig. 2. Images from Malignant class

Due to the great visual resemblance and inner-class vari- ance between melanoma-type and non-melanoma-type skin lesions, automatic skin lesion analysis might be difficult. A precise and effective framework for melanoma analysis must be created because there are no universally accepted diagnostic guidelines. The data preparation process and each model architectural component are described below. Finally, describe in detail the suggested loss function that is employed in the framework.

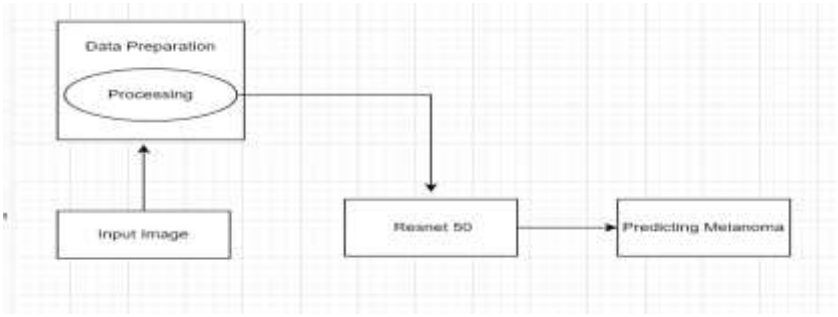

Fig. 3. Flowchart of the proposed model

2.2 Data preprocessing

The dermoscopic image is forwarded to the data preprocessing stage, where the fundamental aspect of this model's hair removal is taken into consideration. Grayscale conversion, kernel construction for morphological procedures, blackhat operation, thresholding, and inpainting are all necessary.

1. Grayscale conversion: The input image is in RGB format, so the image is converted to grey for dimension reduction and to reduce model complexity. 10x10x3-pixel RGB pictures 300 input nodes will be present in the input layer. The same neural network, however, will only require 100 input nodes for grayscale photos.
2. Kernel construction for the morphological procedure: The image's shape is determined by the structuring element or kernel; in this case, the structuring element is a rectangular matrix. Here 1 is used as a structuring element, and the matrix is 17x17.
3. Blackhat operation: This morphological procedure is one of many. In contrast to a bright background, it highlights the interesting dark object.
4. Thresholding: The thresholding process is employed in images to transform pixels with values greater than the threshold value, which in this case is 10 and is replaced by 255. The values 0 and 255 represent black and white, respectively.
5. Inpainting: Reconstruct the chosen portion of the image using pixels near the boundary, then delete any undesirable objects.

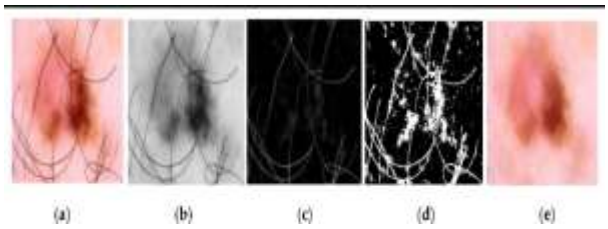

Fig. 4. Images in the different stages of data preprocessing (a). Input im- age, (b). Grayscale image, (c). Blackhat image, (d). Threshold image, (e). Inpaint image

After these steps, the hair from the original image is removed. The benign image with hair is called 77.jpg, while

Fig. 5. Images after hair removal

the image that has been preprocessed to remove hair is called pre77.jpeg. And test.jpg is the cancerous image with the hair follicles, whereas pre-test.jpg is the outcome after hair removal.

2.3 Model

Our model detects and classifies melanoma, so here we use the ResNet-50 architecture for prediction and classification. A 50-layer convolutional neural network called ResNet-50 consists of 48 convolutional layers, one MaxPool layer, and one average pool layer. The remaining blocks are stacked to create networks in residual neural networks, a type of artificial neural network (ANN). Here, only four layers are used for our model. It is the smaller portion of ResNet-50 for performing identity mapping. In addition, they allowed the non-linear layers to fit a different mapping, denoted as F(x), while expressly allowing the layers to fit a residual mapping, which they designated as H(x): The original mapping becomes H(x):=F(x)+x. The model did not require the addition of any new parameters, and the computational time was kept under control. ResNet-50 contains 1x1 and 3x3 convolution layers in a top-down and bottom-up approach.

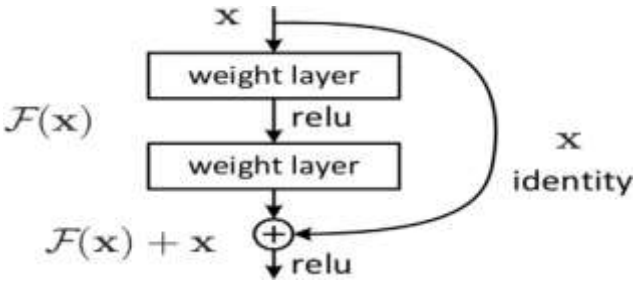

Fig. 6. Shortcut connections that simply perform identity mappings in ResNet 50

After image resizing and data generation, it will be entered into ResNet 50, where the pixel value is reduced by half in each layer for extracting the main features for detecting and classifying melanoma. The pixel size in the layers is as follows: 2048x1024x512x256. The last layer is used to measure the architecture, border, colour, and size of the melanoma. So based on these features, the melanoma can be detected and classified as benign or malignant

3. Results and Discussion

This model gives a better prediction and classification for melanoma, and importantly, the hair follicles are removed from the original image to classify the skin lesion. A model's accuracy is calculated by dividing the total number of forecasts by the total number of accurate predictions it produced.

The proposed model obtained an accuracy of 86%. Precision- Measure the accuracy of the positive predictions.

Precision = TP (2)

TP + FP

Recall -Measure of the completeness of the positive prediction-

F 1 Score = 2 ∗ Precision ∗ Recall (4)

Precision + Recall

Models obtained precision, recall, and F1-score as 86 %. Since F1- the score is 0.86 which is closer to 1, the model is having a better performance.

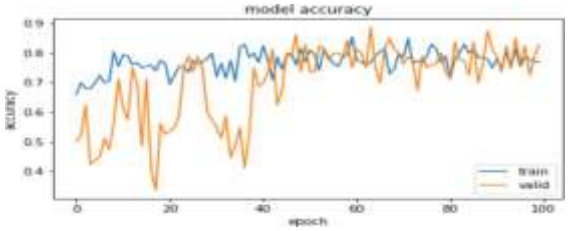

Fig. 7. Accuracy obtained from the model

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

F1 score-Indicated whether the model has a good balance of precision and recall.

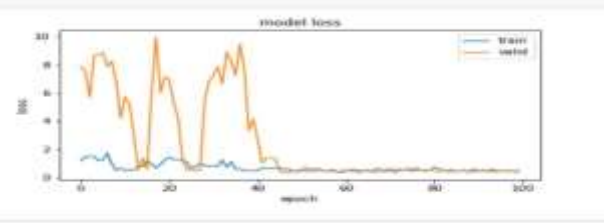

Fig. 8. Loss obtained from the model

Different datasets, like PH2, DermIS, DermQuest, ISBI 2016, and ISIC 2017, are used in different methods. Different researchers propose different methods. They check a single task, like segmentation, classification, or detection. A convolutional neural network is used for the detection of melanoma from images. It is an effective method because CNN can predict melanoma from each pixel, but it requires a large number of labelled parameters for detection in the medical field, which is difficult. SVM and KNN classifiers are used for classification. A popular classifier for accurate and efficient categorization is the Support Vector Machine (SVM). In computer-aided diagnosis systems used by skin cancer specialists to detect melanoma early and save lives, SVM exhibits great accuracy in classifying clinical photos of melanoma (skin cancer). The SVM classifier only takes a small number of images for testing and only considers the ideal condition, not the test images. Different segmentation techniques are used, like the OTSUs method, threshold-based segmentation, and template matching techniques like that. Different frameworks are used for identifying melanoma. They can't effectively segment the pictures to extract the characteristics. If we correctly remove the noise from the images, the segmentation result will be accurate. Some methods remove the noise, and some do not, so it will affect segmentation. Due to the apparent resemblance between skin lesions and normal skin, certain approaches can't accurately diagnose melanoma. But the end-to-end framework for analysing melanoma can provide proper segmentation, classification, and detection. In this method, they use ResNet 50 for feature extraction, and it can also classify and label the object in the image. Furthermore, the hair follicles in the image are removed.

4. Conclusion

Offer a unique end-to-end multi-task framework that can concurrently categorise and identify skin lesions. Without requiring any further post-processing steps, the framework may output the melanoma kind, position, and border from a picture of any size as the input. The usefulness and precision of the suggested framework are demonstrated by experimental findings using the skin cancer benign vs. malignant dataset.

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