Skin Cancer Prediction Using Image Processing and Deep Neural Network

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1. Project Overview

Skin cancer these days have become quite a common occurrence especially in certain geographic areas such as Oceania. Early detection of such cancer with high accuracy is of utmost importance, and studies have shown that deep learning- based intelligent approaches to address this concern have been fruitful. [1]

The quicker the ability to detect accurately where a lesion is malignant will aid in providing fast and effective treatment. When detected early, the 5-year survival rate ranges between 89 and 95% for stages I and II with peaks of 99% for stage 0, while it decreases to 25–70% for stage III and only 7–20% for stage IV. In this regard, early diagnosis is particularly important as early-stage melanoma can usually be removed with minor surgery [2] .

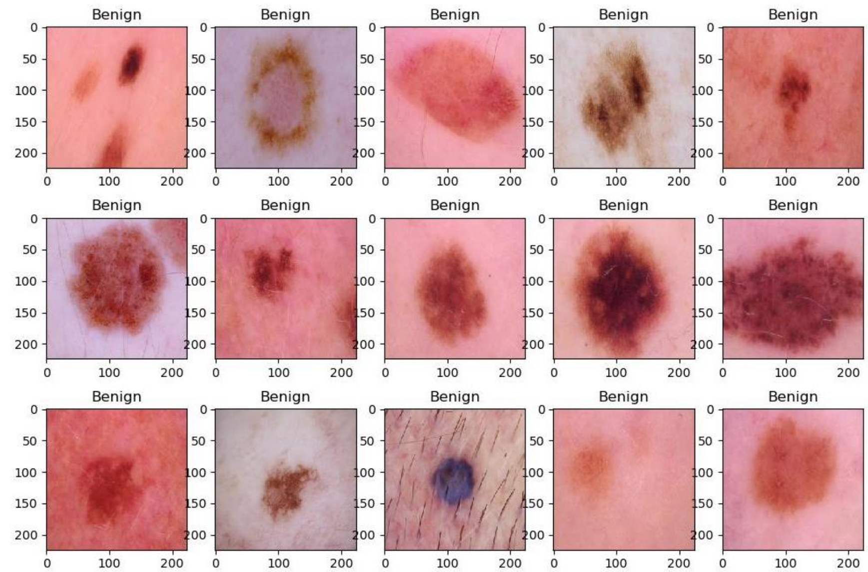
In this project, we use image processing techniques in order to improve the quality of skin lesion images and then using deep neural networks, to predict if the lesion is cancerous or not.

The dataset is ISIC (The International Skin Imaging Collaboration) that includes skin lesion images in benign and malignant categories.

2. Dataset information

The dataset is taken from the ISIC (International Skin Image Collaboration) Archive. It consists of 1800 images of benign moles and 1497 images of malignant classified moles. The images have all been resized to low resolution (224x224x3) RGB.

Below, some of the images from the dataset and the category that they belong to, is observed.



3. Preprocessing

Medical imaging datasets usually have some unwanted regions. Not only this, for doing any process on those images, a high level of clearance of images is needed to be able to identify benign and malignant skin lesions. In this work different preprocessing techniques will be evaluated to find the best performance for cancer prediction for our dataset.

The algorithm will be explained in the following section.

The idea is to use a combination of digital hair removal and rolling ball technique followed by a filter to process the original images. At the end, an erosion followed by dilation was applied to images.

3.1. Digital hair removal

As hair or unwanted lines on the images can interfere with detection, it is better to remove them at the beginning.

We remove hairs from our images by applying the DHR algorithm. This consists of four steps: Grayscale, Morphological BlackHat transformation, creating the mask for InPainting, and the InPainting algorithm. [1]

3.1.1. grayscale

As the name suggests, converts the color images to images containing only shades of gray to simplify the algorithm and reduce computational requirements.

This can be achieved using cv2.cvtColor () of Python OpenCV.

3.1.2. Morphological BlackHat transformation

We apply the BlackHat morphological operation on the gray scale images, since BlackHat operators are more suited for grayscale images.

Black-hat transform is an operation that is used to extract small elements and details from given images and is defined as the difference between the closing and the input image.

For hair detection, a structuring element of size 23 × 23 is utilized for this morphological operation.

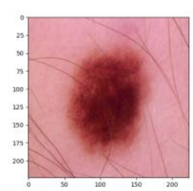
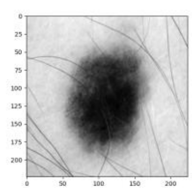
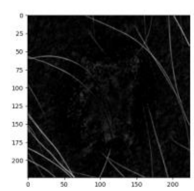
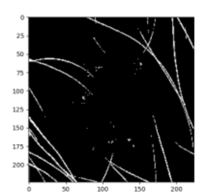
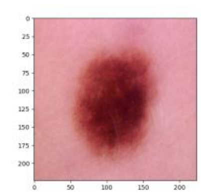
3.1.3. Intensify the hair contours

The output from BlackHat Morphological operation results in image with variations of grayscale intensity. To increase the contrast of the hair regions, a binary thresholding is applied. If the pixel value is smaller than 10, it is set to 0, otherwise it is set to a maximum value (255).

3.1.4. Inpainting algorithm

The Inpainting algorithm refers to the reconstruction of small missing and damaged portions of images. This activity consists of filling in the missing areas or modifying the damaged ones in a way that is not detectable to an observer who is not familiar with the original images.

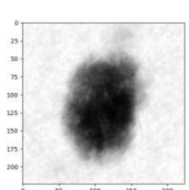
Image inpainting works by replacing the damaged pixels with pixels similar to the neighboring ones, therefore, making them inconspicuous and helping them blend well with the background. First, we require a mask that in our case is the threshold image, which is essentially a black image with white marks on it to indicate the regions which need to be corrected.

Original image	Gray scale	Morphological blackhat operation	Threshold (mask)	Inpaint
				

3.2. Rolling ball technique

We apply the rolling ball technique in order to remove background noise.

The rolling ball algorithm is a well-known tool to correct non-uniform brightness, especially in medical images. It is frequently used in biomedical image processing and was first proposed by Stanley R. Sternberg in 1983. This algorithm has successfully been applied to medical images plotted as a 3D surface, with the pixel value of the image being the surface height. A ball of a user-defined radius is rolled over the backside of the surface creating a background surface and subtracting this background surface from the original image removes large spatial variations of the background intensities. [1]

Rolling ball


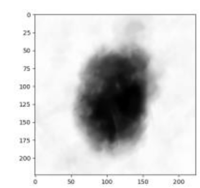
3.3. Applying filters

Subsequently, some well-known filters are checked on the dataset to find the best one that can increase the performance of our model.

3.3.1. Non-local means filter

Non local means filter is a filter that removes noise but preserves the edges. It looks at all the pixels of the image and weights them based on how similar they are to a pixel p. unlike Bilateral filter, the supporting windows is not around p but it is the whole image.

Non local mean filter with h= 3

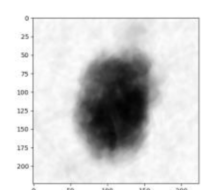


3.3.2. Median filter

It is a non-linear filter that each pixel intensity is replaced by the median over a given neighborhood, the median being the value falling half-way in the sorted set of intensities.

It contracts impulse noise effectively as outliers tend to fall at either the top or bottom end of the sorted intensities. It will not introduce blur, because it doesn’t introduce new values in the middle.

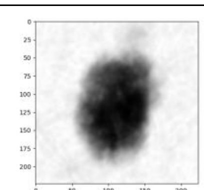
Median filter with k = 5



3.3.3. Mean filter

Mean filters have a simpler structure compared to median filters. They replace the value of every pixel in an image with the mean (“average”) value of its neighbors. This has the effect of eliminating pixel values which are unrepresentative of their surroundings.

Mean filter with k=5



3.4. Morphological operation

Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. Erosion, dilation, opening, closing: The four basic morphological operations together with some others can be implemented on a binary image.

3.4.1. Erosion

Erosion is a fundamental morphological transformation of image processing. The value of the output pixel is the minimum value of all pixels in the neighborhood. In a binary image, a pixel is set to 0 if any of the neighboring pixels have the value 0.

Morphological erosion removes floating pixels and thin lines so that only substantive objects remain. Remaining lines appear thinner and shapes appear smaller.

3.4.2. Dilation

Dilation, another fundamental morphological operation, adds pixels to the boundaries of objects in an image. Dilation has the opposite effect to erosion; it adds a layer of pixels to both the inner and outer boundaries of regions.

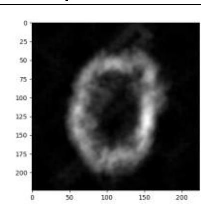
The value of the output pixel is the maximum value of all pixels in the neighborhood. In a binary image, a pixel is set to 1 if any of the neighboring pixels have the value 1.

Morphological dilation makes objects more visible and fills in small holes in objects. Lines appear thicker, and filled shapes appear larger.

This erosion followed by dilation is also called opening an image which is a binary image. Opening can be thought of as comparing the structuring element to foreground parts so as to remove those which turn out different and keep unaltered ones.

3.4.3. Morphological gradient

A morphological gradient, is the difference in mathematical morphology between the dilation and the erosion of a given image and digital image processing. It is an image where each pixel value indicates the contrast intensity in the close neighborhood of that pixel.

Morphology operations


4. Building a prediction model

After the preprocessing step, we use the output images to train a deep neural network to build a prediction model for cancer detection.

We used a convolutional neural network to compare the results of different algorithms.

```
input_shape = (224,224,1)

model = Sequential ()

model. add(Conv2D(32, kernel_size=(3,3),activation='relu' ,padding = 'Same' , input_shape=input_shape))
model .add(Conv2D(32,kernel_size=(3,3), activation='relu',padding = 'same'))
model. add(MaxPool2D(pool_size=(2,2)))
model. add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), activation='relu',padding ='Same'))
model. add(Conv2D(64, (3, 3), activation='relu',padding ='Same'))
model. add(MaxPool2D(pool_size = (2, 2)))
model. add(Dropout(0.40))


model.add(Flatten())
model.add(Dense(128, activation='relu'))
model. add(Dropout(0.5))
model. add(Dense(num_classes, activation='sigmoid'))
```

5. Result

At the time of training the model, the rolling ball technique was taking too much time to process and it was not possible to use it for our purpose, so we had to remove it from the preprocessing steps.

The preprocessing algorithm includes following steps: DHR + filter + morphological operations

Preprocessing steps	Training accuracy	Validation accuracy	Training loss	Validation loss
No preprocessing	0.72	0.69	0.57	0.54
DHR + mean filter + morphological operations	0.75	0.76	0.52	0.50
DHR + median filter + morphological operations	0.82	0.75	0.42	0.54
DHR + non-local mean filter + morphological operations	0.81	0.77	0.43	0.53

As observed in the table, the results with non-local means and median filter are showing better results than the mean filter.

As expected, the mean filter (being a linear filter) reduces noise but blurs the image. The non-local mean and median filters, on the other hand, are non linear filters and although they apply more computational cost, but have a better performance on preserving the edges that is useful in our case.

6. Conclusion and Future Work

The model successfully predicts an image to be benign or malignant with validation accuracy of 77%, and loss of 0.53. However, it still needs to be improved, specially in the medical field, the results need to have much higher accuracies.

To further improve the model, following actions can be taken:

- Applying other image processing techniques, for instance using local binary pattern, or other noise removal filters
- Increasing the training dataset by data augmentation or using other available datasets such as HAM10000.
- implementing other deep neural network models, for instance pretrained models such as ResNet
- Using patient information into account can also help to have a better and more accurate prediction

7. Reference

[1] S. A. R. Q. A. K. F. M. J. M. S. S. K. B. M. J. K. M. H. K. A. Pronab Ghosh, "SkinNet-16: A deep learning approach to identify benign and malignant skin lesions," *Frontiers in Oncology ,* 2022.

[2] A. I. I. F. I. F. C. O. J. A. D. A. Gálvez, "NURBS functional network approach for automatic image segmentation of macroscopic medical images in melanoma detection," *Journal of Computational Science, Elsevier,* 2021.

[3] "OpenCV Documentation," [Online]. Available: https://docs.opencv.org/4.x/.

[4] "Kaggle,"[Online].Available: https://www.kaggle.com/code/fanconic/cnn-for-skin-cancer-detection/notebook.