International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:15, No:8, 2021

A Convolutional Deep Neural Network Approach for Skin Cancer Detection Using Skin Lesion Images

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Abstract—Malignant Melanoma, known simply as Melanoma, is a type of skin cancer that appears as a mole on the skin. It is critical to detect this cancer at an early stage because it can spread across the body and may lead to the patient death. When detected early, Melanoma is curable. In this paper we propose a deep learning model (Convolutional Neural Networks) in order to automatically classify skin lesion images as Malignant or Benign. Images underwent certain pre-processing steps to diminish the effect of the normal skin region on the model. The result of the proposed model showed a significant improvement over previous work, achieving an accuracy of 97%.

Keywords—Deep learning, skin cancer, image processing, melanoma.

I. Introduction

SKIN cancer is the most common type of cancer over the world. According to the American Cancer Society, Melanoma is a type of skin cancer that generally starts in certain skill cells called “Melanocytes”. Melanocytes are the skin cells that produce brown pigments which give the skin its color. Melanoma cancer can be also referred to as “Malignant Melanoma” or “Cutaneous Melanoma”. Although this type of skin cancer is less common, it can spread to other parts of the body, the thing that makes it more dangerous [1]. Similar to other types of cancer, Melanoma can be diagnosed at different stages. A stage indicates how critical and dangerous the situation is, and what is the suitable cure. An article published by Medical News Today describes a staging method that categorizes Melanoma into 5 stages. Stage 0 is the early appearance of Skin Cancer and Stage 4 indicates the spread of cancer to other parts of the body (Brain, Liver, etc.) [2].

Although Melanoma can spread throughout the body and results in severe consequences, including the death of the patient, this type of cancer is easy to cure if it was detected early (generally at Stage 0). Early detection of diseases, specially cancer, is an ongoing research in the medical field, and experts are always developing more efficient tools for that problem.

Typically, moles that appear on the skin are examined and analyzed to decide whether they are cancerous or benign. Experienced dermatologists are having a hard time ensuring whether a mole on the skin is benign or cancerous. In Dermatology, two different techniques can be followed for this task, ABCD rule and 7-points checklist. The ABCD rule technique indicates the existence of Melanoma based on 5 mole characteristics: Asymmetry, Border Irregularity, Color Pattern and Diameter [3].

7-points checklist depends also on certain mole characteristics and its behavior. Following this technique, dermatologists check how the lesion size is changing, irregular pigmentations, inflammation, crusting, etc. [4].

Given the challenges faced, computerized methods are being developed for the automated detection of cancerous mole. In this work, we are developing a deep learning-based technique that will help dermatologists to classify skin lesion images into cancerous or benign.

The rest of this paper is organized as follow: In Section II we describe previous work that tackled this problem. Data and processing steps are discussed in Section III. In Section IV we introduce Convolutional Neural Networks and describe the methodology followed. Experimental results are introduced in Section V and we finally conclude our research in Section VI.

II. Literature Review

Different Machine Learning techniques and detection approaches were applied to tackle the problem of Melanoma detection.

Following the ABCD rules, [5] extracts features representing the lesion asymmetry, border, color and diameter from skin lesion images. The features are then fed to a Feed Forward Artificial Neural Network model. The images are classified into different classes representing the category of the lesion. These classes are “Melanoma”, “BCC”, “SCC”, “Melanocytic Nevi”, “Seborrheic Keratoses” and “Acrochordon”. The latter three classes represent a begin lesion. In [6], some image processing steps are implemented for segmenting the mole images and extracting the geometric features of such a mole. The extracted features include the mole diameter, border irregularity index and asymmetric index. These mole characteristics is part of the ABCD rule used by dermatologists. Based on the extracted features, a Nearest Neighbor model is used to classify the images as melanoma or benign. Other ABCD based approaches includes [7]–[10]. An SVM based approach is introduced in [11], where the aim is to construct a decision support system that detects the existence of melanoma using only texture information. Texture information is important to study and detect different characteristics in images, such as orientation, regularity, smoothness, etc. A support vector

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machine-based technique is used to detect, identify and classify such information from skin lesion images taken using a Nevoscope device. In [12], the authors try to detect the existence of pigment networks in mole dermoscopic images. Pigment networks can be an indicator for the existence of Melanoma. Set of rules are generated using a machine learning-based process, that can construct a mask of pixels that may represent the pigment network in an image. These masks undergo another process where subcomponents are detected and studied for the existence of pigment network.

Meta-Heuristics are also used to tackle this problem. The work [13] aims to optimize the rulesets produced by C4.5 using a Genetic Algorithms based approach. The authors also follow the ABCD rules technique by extracting the corresponding features from the lesion image, then train their model to detect whether an image is malignant or benign.

Segmenting the skin lesion image is an important step for feature extraction and nose reduction. In [14], the authors develop a clustering based approach to segment skin Lesion with the use of smoothing filters and area thresholding. Preprocessing steps, that include conversion, filtering and contrast adjustment are applied to the dermoscopic images. Then a K-mean clustering approach is applied followed by thresholding and noise reduction steps. The resulted segmentation is compared with the real segmentation by calculating the overlapping score and correlation coefficient.

In the last decade, deep learning approaches have been used in various applications and showed promising results. Applications include Natural Language processing [15], Image Recognition [16], Speech Recognition [17], and many others. The advantage of Deep Learning over other supervised machine learning techniques is the ability to detect and explore deep hidden relationships between the data.

In the problem of Melanoma Detection, Deep Learning approaches, mainly CNN, can have tremendous impact. In [18], the aim is to use deep learning for detection of skin cancer using digital images as input. The methodology introduced in this paper consists first of certain image pre-processing steps in order to decrease the effects of noise and illumination. The processed images are used to train a CNN. However, given that CNN needs a lot of training power in order to result in highly accurate predictive model, the original dataset is expanded following some images augmentation techniques. Results were benchmarked against three previous studies done on the same data. These studies include [19] which is one of the first reported work, and used as a baseline, [20] an example of a used commercial tools and [21] which classify cases in a semi-supervised framework. The authors [22] employ a two-stage model that can be used for automatic skin lesion images segmentation and melanoma detection in such images. The CNN model proposed is enhanced further to be work on a limited training set by using effective training schemes, and by increasing the network depth. The work [23] also consists of a pretrained CNN that was trained for a medical classification task referred to as Retinopathy. The model is used to perform two classification tasks. Malignant vs Benign in which a malignant case can represent melanomas or basal cell carcinomas. All other types are considered benign. In the second task, the basal cell carcinomas cases are removed from the data set, and the task is to classify images as Melanoma or Benign.

The main challenge when using deep learning is that its classification power depends on the amount of data used. In general, it is hard to get enough data for specific problem to train a CNN model, especially when dealing with medical images. To overcome this challenge, some research use transfer learning [24] in order to use pre-trained networks. For example, the work in [25], uses a CNN that is pretrained on natural images to classify skin lesion images based on the lesion type. In this context, lesions are grouped into 10 different types that represent benign, melanoma and non-melanoma cancer cases. The work [26] consists of using CNN features which are trained in the domain of natural photograph. This CNN model is further combined with unsupervised learning features based on sparse coding and SVM classifier. The developed approached is used to distinguish melanoma lesions from all non-melanoma images, and also between melanoma and atypical cases only. Deep learning is also used for the automated segmentation of skin lesion image. Such work can be found in [27] and [28].

III. Data and Data Pre-Processing

A. Data Description

Data consists of images of skin lesion. An image can represent a benign case or a malignant one. In order to compare and benchmark our proposed model with previously published approaches, we used the MED-NODE dataset [21]. This dataset consists of 170 images in which 70 images represent melanoma cases.

B. Data Pre-Processing

In order to improve the efficiency our model and remove all unwanted features from images, a set of image pre-processing steps were followed.

1) Contrast Equalization: Images are usually taken under different circumstances and form different sources. Hence, illuminating the effects resulted from this is important. One important step is to enhance the contrast of such images in order to reduce the lightning effect on them. Such enhancement will basically adjust the intensity of the image and is known as histogram equalization. Fig. 1 shows the effect of histogram equalization on some images.

2) Image Segmentation and Region of Interest Extraction: Typically, each lesion image in the used datasets consists of two different regions: the normal skin and the mole that is located on such skin. The normal skin part of the image should not have an effect on the classification; hence it is important to make our model insensitive to such region. These normal skin regions may differ from one image to another in terms of skin color, existing/absence of hair, etc. Image segmentation is used in order to locate our region of interest. We used the Cluster based segmentation (k = 2) followed by binary image filling to fill certain holes. Having done so, we keep the mole as is and replace all the normal skin pixels by black pixels. The resulting images will be fed to our deep learning model

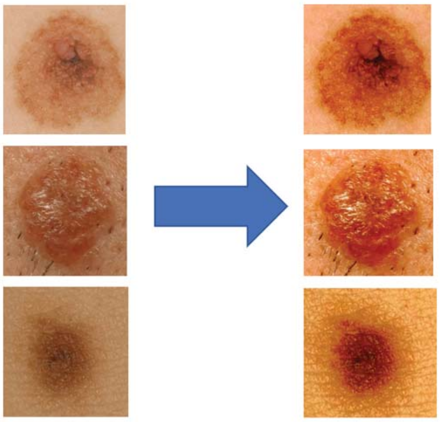

Fig. 1 Example of histogram equalization

for training and classification. By following this methodology, the input images will only consist of the mole without the surrounding normal skin region, which will lead our model not to be affected by such region. Fig. 2 shows the transformation of an image.

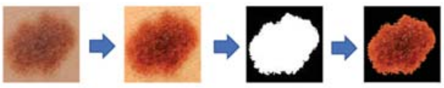

Fig. 2 Example of an image pre-processing flow

IV. Methodology

A. Convolutional Neural Networks

CNN is a deep learning algorithm based on a grid-like topology [29]. What makes CNN different from other neural networks inspired techniques is the use of a specialized matrix operation known as convolution instead of performing matrix multiplication. One advantage of CNN is that it automatically extracts features from the input images and then it uses these features to perform classification/regression. We can represent CNN as a set of successive convolution and pooling operations that are performed on the input images. Convolution uses certain kernels to filter the images [18]. The pooling layer is used for extracting the general patterns from the convolved images. It replaces the element at a specific location by the arithmetic summary of the neighborhood [29].

B. Melanoma-CNN

In this paper, we develop a CNN, referred to as Melanoma-CNN , for the aim of classifying skin lesion images as melanoma or not. Our model consists of two convolving layers each followed by a pooling layer. The last part of the model consists of two fully connected output layers. The first pooling layer performs max pooling; however, the second performs average pooling. We used the “relu” activation function (except for the last output layer where we used the softmax function). Our model was developed using Keras. Fig. 3 shows the general strucutre of Melanoma-CNN.

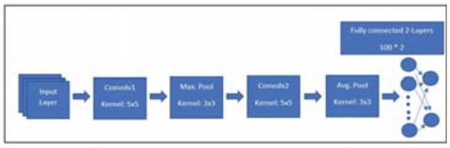

Fig. 3 Melanoma-CNN Architecture

V. Experimentation and Results

After performing the abovementioned pre-processing steps, we ran our deep learning model on the resulted images. In order to have a more stable model, we performed 10-folds cross validation. Cross-Validation is done by dividing the main images dataset into 10 different chunks (folds). At each time, we train our Melanoma-CNN using 9 folds and we test on the remaining one. This is repeated 10 times. We report, the average accuracy of our model in Table I compared to previous work.

TABLE I
The Results of Our Deep Learning Model Compared to Previous Published Work

Model	Accuracy
CNN [18]	0.81
Neural Networks [19]	0.70
Spotmole [20]	0.67
Melanoma-CNN	0.97 (0.01)

As can be seen from the results, our model achieved an accuracy of 97% outperforming previous work that tackled this same problem using the MED-NODE data set. Melanoma-CNN also shows a low standard deviation of 0.01 which describes the stability of this model. In addition, and to test the effect the histogram equalization taken in the pre-processing phase, we re-ran our model without performing this step. In other words, we segmented and extracted the region of interest without doing contrast enhancement. This lead to a decrease in the model accuracy (93%). This fact shows the importance of doing contrast stretching as it diminishes the effect of illumination on the deep learning model.

VI. Conclusion

Melanoma is a skin cancer disease that can spread across the body and results in severe and deadly consequences. However, when diagnosed at an early stage, Melanoma can be cured which render the early detection of such disease as highly important. We used a deep learning-based model in order to automatically distinguish between cancerous and non-cancerous skin lesions. We used skin lesion images in order to train and test our model. The deep learning model was preceded by a sequence of image processing steps in order to enhance the image intensity and to locate the region of interest. Our model achieved an accuracy of 97% after 10-folds cross validation. This results when compared to previous work showed a huge improvement over previously published result. In the future, we plan to use different dataset with more cases in it as well as doing multiclass prediction in order to classify different skin cancer types as well.

ACKNOWLEDGMENT

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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