Using Local Binary Patterns and Convolutional Neural Networks for Melanoma Detection

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Abstract. Skin cancer is an abnormal growth of skin cells on body parts which get more exposure to sunlight. Detection of cancer in early stages improves patient outcomes, however, manual assessment of medical cells and microscopy images is laborious work, and the results are often subjective so that the agreement between viewers can be low. In this paper, a new method is proposed to detect skin cancer signs such as asymmetry, border, colour and diameter using segmentation and region analysis. Melanoma and non-melanoma skin cancer images have been classified using region analysis, boundary, colour and size measurements. To achieve accurate and computationally efficient results, Local Binary Pattern Convolutional Neural Networks are employed. The proposed method has provided a high classification performance, achieving 0.95 accuracy rate, 0.95 sensitivity, and 0.96 specificity on the ISIC public data sets.

Keywords: Convolutional Neural Network, Local Binary Pattern, Classification

1 Introduction

Early detection of skin cancer diseases is critically important because of their high prevalence. Only in USA 91,270 new cases (51,150 male and 36,120 female) have been registered in 2018 and 9,320 deaths were reported [1]. Detection of skin cancer is not easy without laborious clinical and laboratory tests, therefore, consideration of efficient tools using image processing and machine learning techniques to detect pathologies from the images has gained significant importance in recent years [2–4].

Skin cancer is the most prevalent cancer in fair-skinned people. It is an uncontrolled rapid growth of abnormal skin cells which is usually caused by exposure to ultraviolet light either from sun or from man made sources [5]. The incidence of skin cancer has been rapidly increasing over the past decades. Skin cancer affects one out of every three cancer patients, and one in five Americans will be affected during their lifetime according to the American Academy of Dermatology [6].

There are three main types of skin cancer. The first is Melanoma which can occur on any skin surface, but is rare in the dark-skinned population [7, 8]. The

second is Basal cell skin cancer which begins in the basal layer of the skin and is most common in the fair people. The third type is Squamous cell skin cancer which begins in the squamous cells of the skin which is not exposed to the sun such as on legs or feet, and it is usually common in dark people [9].

The rest of the paper is organised as follows: Section 2 introduces the basic idea of skin cancer detection. Section 3 describes the proposed framework, Section 4 presents the paper discussion and results. Section 5 concludes the paper and finally discusses the future work.

2 Background

Malignant melanoma is the most dangerous of skin cancers arising from the cells that give the skin its colour (melanocytes) and has a high tendency to spread to other parts of the body [10, 2]. If the diagnosis of malignant melanoma is achieved in its early stages, then a potential reduction in the risk of death is possible [2, 3].

Computer vision and machine learning algorithms are used to achieve the early detection of melanoma and many authors have reported plausible results [2]. Such systems can assist us to distinguish between benign (non-cancerous) and malignant lesions. A common approach [11] used by doctors in ascertaining the diagnosis can include the following diagnostic signs as markers: asymmetry, boundary irregularity, colour and skin lesion diameter (which is known as ABCD analysis), which provide useful clinical assessment [10].

Due to malignant melanoma, the structure of skin cells is disturbed, and the skin pattern is disrupted. As a feature set, disruptions of the skin pattern are used to find out whether it is a malignant or benign skin lesion. In relevant research, normal white light clinical images are used to extract the skin pattern by high-pass filtering [12] and skin line direction, and for lesion classification, the skin line intensity and local isotropy have been used for processing a small image set [13, 14].

Image acquisition, preprocessing, feature extraction and classification are the basic steps of processing algorithms [15–18]. In [2] a simple algorithm has been proposed for skin cancer detection using pre-processing with a median filter, segmentation using thresholding and fuzzy c-means, and in the third step, feature extraction is done by Gray Level Co-occurrence Matrix and contour signature. The image processing with a median filter is useful to remove unwanted hair and noise from the images.

Review of relevant literature shows that ABCD (asymmetry, boundary irregularity, colour and diameter of skin lesion) have not yet been used as features in detection of melanoma. The new features should be combined with known features in order to enhance classification performance. If the skin pattern features and ABCD features are combined, then the lesion discrimination is expected to increase in comparison with that achieved with conventional features alone. First of all two features will be extracted from skin pattern, then the compu-

tational algorithms will be used to calculate the ABCD features, and last, the lesion classification will be conducted using individual and combined features.

Several research groups have achieved promising results on melanoma detection in dermoscopy images using Convolutional Neural Networks (CNNs). Different techniques and methods are used to classify skin lesion images, [19] analyse texture in skin images, apply standard statistical methods. [20] used Wiener filter to remove noise and thresholding to segment the whole images. [21] have used a CNN framework with morphological operations for preprocessing and segmentation and achieve a plausible result.

Some of the most intensively explored research areas are Machine Learning and Computer Vision [22–24]. Within our framework benchmark data sets are used to develop a decision-making system. Such a system is expected to provide most reliable outputs against the given inputs [25]. The shortcomings of such systems have been resolved using deep learning algorithms, such as CNNs, Fully Convolutional Residual Networks [26, 27].

The convolutional layer of CNN generates the output derived from the input by using filters or kernels [27]. Each layer output node is the following layer's input. The number of filters with the given settings is determined by the size of images or data sets. The pooling and fully-connected layers are used by a CNN to process the images.

A layer of CNN is fully connected, so that its nodes are connected to the nodes from the adjacent layer. A CNN with 16,384 neurons is required for a 128x128 pixel image. An input is passed to the adjacent layer neurons through weighted connections, and finally the output is computed at the output layer [28].

To overcome the constraints of memory and computation time, approaches such as MapReduce and Hadoop are used to get efficient results. The use of a distributed model enables us to analyse and classify patterns and the find meaningful information from a large data set within a short time.

3 Proposed Framework

In this paper, a CNN-based framework is proposed to explore the main preprocessing task on the ISIC 2017 skin cancer image data set [29]. Before using CNN, the following image processing steps are used as follows.

3.1 Image Preprocessing

The non-uniform illumination is adjusted by using gamma correction. Then images are resized and contrast and brightness are adjusted. Colour images are converted into grey scale by using $\mathrm{GrScImg}_(x, y)$ defined by Eq. 1. Colour is not essential for detecting patterns and unnecessarily increases the computational expenses, and thus each pixel is analysed as follows:

$$GrScImg_{(x,y)} = \frac{1}{3}\sum_{z=1}^{3} img(x, y), \tag{1}$$

where $\text{img}(x, y)$ is a grey-scale image.

To refine the data set, filtering algorithms are used as follows. Eq. 2 $\text{GBImg}_{(x,y)}$ is the Gaussian filter, $ck(k, l)$ is the kernel and $\text{GrScImg}_{(x,y)}$ is the grey scale image, which are capable of plausibly remove unwanted artefacts (hair, noise, and bubbles) from the images:

$$GBImg_{(x,y)} = ck(k, l) \otimes GrScImg_{(x,y)}. \tag{2}$$

Edge detection algorithms (Canny and Sobel) provided the best result compared to others. After detection of edges ($\text{IMed}_{(x,y)}$), an image with a sign of shape of a lesion $\text{IMLes}_{(x,y)}$ is processed in Eq. 3 to remove artefacts which are caused by the skin lesion:

$$IMeL_{(x,y)} = IMed_{(x,y)}IMLes_{(x,y)}. \tag{3}$$

After removal of the artefacts, the next step is the morphological operation applied to the open shape of skin lesion by using a structuring element with $R = 2$.

3.2 Image Segmentation

Automatic thresholding [30] and masking operations in RGB colour mode are performed by applying a binary mask for each of the colour channels. In the ISIC data set there is no easily detectable shape of skin lesions (some portion of skin can be more prominent than a cancer lesion, some images have no proper border, some skin lesions have no noticeable difference from the skin (cancer lesions on dark skin). Thus using such a segmentation, a proper shape of the cancer lesion can be accurately specified so that the artefacts can be efficiently removed.

A morphological operation is applied with four morphological operations erosion, dilation and Top-Hat transform capable of extracting tiny and bright/dark features from a data set, and Bottom-Hat transform to obtain information about surface, size and edge of the images. Eq. 4 describes the Bottom and Top-Hat problem, where `img` is a smooth image and `Ker` is a structuring element.

$$BHImg = img - (img \circ Ker). \tag{4}$$

For segmentation, edge detection and region growing are used to find the size of a lesion in an image. Before applying segmentation, the closing and opening methods are used to achieve the plausible result in region growing segmentation.

3.3 Feature Extraction

Geometric Features (Area, Perimeter, Greatest Diameter, Circularity Index, Irregularity Index) are used to extract feature of melanoma skin lesion. To extract geometrical features, the segmented image is analysed which contains only the skin lesion. The greatest diameter is estimated as follows:

$$(x_c, y_c) = \left(\frac{\sum_{i=1}^{n} X_i}{n}, \frac{\sum_{i=1}^{n} Y_i}{n} \right), \tag{5}$$

where x_i and y_i indicates the coordinates of the ith lesion pixel, and n is the total number of lesion pixels.

3.4 Local Binary Patterns

Using the above processing, textures which are based on Local Binary Patterns (LBPs) are used. LBPs are used to detect or classify the abnormality in skin lesions. The user-defined parameters are required to set the number of neighbours P and the radius of comparisons R, as outlined below:

$$LBP_{P,R} = \sum_{P=0}^{P=1} (s(g_p - g_c)2^p). \tag{6}$$

The above g_p and g_c represent the neighbour and central pixels of the grey scale value, respectively. The P and R are the total neighbour pixel values and radius of the neighbourhood, respectively. The centre value is compared with a neighbour pixel value. When the centre value is less than the neighbour value, then $s = 1$, otherwise $s = 0$.

Local Binary Convolutional Neural Network [31] is used to achieve highly efficient statistical and computational result. It is a hybrid combination of constant and learned weights, which generalises the basic LBP within the following settings:

Base: it takes any real values for weights to encode an LBP descriptor,

Pivot: to compare the patched intensity of the pixel, it chooses the centre value as a pivot. Choosing different intensity values in the patch will give different local textures, and

Ordering: it partially encodes the local texture for a specific order by choosing a different neighbourhood size and a pivot value.

4 Results and Discussion

The Local Binary Convolutional Neural Network [32] is used with hidden layers and Leaky ReLu, Dropout, Batch Normalisation and Flatten Layers. The use of the proposed LBCNN and preprocessing has enabled a high diagnostic accuracy to be achieved.

The LBCNN has been trained with the 33 layers including the (2x2)-max pooling layers along with the Dropout and Batch Normalisation layers. The fully connected layer has a padding value of 1. A batch size is set to 50 and the neural network is trained with an ADAM algorithm [33]. Overfitting problem was mitigated by the dropout layer with a factor of 0.2. The Leaky ReLu layer is used to reduce the gradient problem in the convolutional layers. The LBP equation returns the minimum value of circularly rotated images.

The images of a 128x128 dimension are fed into the input layer to be convoluted with 33 layers using the Leaky ReLu activation to rectify the gradient problem. To overcome the covariance shift and to speedup the training process, the batch normalisation is applied which is widely used in Deep Learning. The LBCNN has been trained with different ratios on the ISIC data including a random set of 7,560 images 45% of which were classified without melanoma and the remaining 55% with melanoma. For validation and testing 2,000 images have been chosen in the same proportion of the pathological cases. The resultant accuracy rates were 0.95 on the training and 0.94 on the test sets. Precision rates were 0.95 and 0.93, recall 0.95 and 0.95, specificity 0.95 and 0.93, sensitivity 0.95 and 0.95, respectively.

The ratio of the training and validation images has been changed to 50% of non-melanoma and 50% with the melanoma. In this case, the training and testing accuracies were 0.95 and 0.95, precision 0.95 and 0.96, recall 0.95 and 0.95, specificity 0.96 and 0.96, and sensitivity 0.95 and 0.95, respectively.

The proposed framework has been compared with existing solutions [34, 35]. The comparison has shown an improvement in the accuracy and specificity, but not in the sensitivity which was higher for the techniques developed in [36, 37].

5 Conclusions and Future Work

Skin cancer is a life threatening pathology, detection of which at early stages can improve patient outcomes. The manual expert analysis is laborious, whilst expert opinions can be unreliable.

The new method has been proposed to improve the accuracy of detecting the skin cancer signs such as asymmetry, border, colour and diameter by using the image segmentation and analysis of regions of interest. The melanoma and non-melanoma skin cancer images have been detected by using the region analysis, boundary, colour and size measurements.

The improvement has been achieved by using the Local Binary Pattern (LBP) and CNNs. In our experiments on the ISIC public data sets the proposed method has achieved 0.95 sensitivity and 0.96 specificity. Parameters of LBP have been explored with different textures in regions of interest.

The future work plans are to explore ways of increasing the sensitivity of the proposed method, keeping a high specificity value. The proposed CNN framework can be also extend on images which can be obtained in real time by using phone cameras. This will require experiments with new settings for a CNN to find a reliable solution.

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