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Texture analysis for skin cancer diagnosis using dermoscopic images

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Abstract

This paper provides a foundation to examine the dermoscopic images for skin cancer diagnosis. A dermoscopic image will often include textured areas that make up a major amount of the image. It is conceivable to organize and categorize such textures according to whether they are related with artifacts or if they reflect biological structure. Given the connection between structure, disease, and texture, it seems likely that quantitative measurements of texture might make it possible to characterize the tissues included inside a dermoscopic image. It has been shown that texture is a valuable characteristic for the characterization of skin cancer in dermoscopic images. The proposed system is comprised of two stages: the first is the extraction of information or features from dermoscopic images, and the second is the categorization of those images using a decision tree classifier. Based on the findings, it is possible to draw the conclusion that the extracted features have kept all of the information presents in the dermoscopic image that provides an overall accuracy of 98.89%

Keywords

Skin cancer, dermoscopic images, textures, image analysis, computerized systems

Imprint

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1. Introduction

The epidermis and the dermis are the two primary layers of the skin. The epidermis is the outermost layer (mesodermal origin). The previous layer is a structure made up of many layers. Keratinocytes, also known as epidermal cells, are the primary kind of cell found in the epidermis. The epidermis continually renews itself as a result of cell division occurring in its most superficial layer, which is referred to as the Basal Layer (BL). As the cells in the prickle cell layer move closer and closer to the skin's surface, they produce increasing amounts of the fibrous protein keratin. The prickle cell layer is made up of cells that have undergone cell division. The time it takes for a cell to go from the basal layer (BL) to the surface of the epidermis, known as the epidermal transit time, is roughly 30 days. The ectoderm of the embryo gives rise to the appendages of the epidermis, such as sweat glands, nails, sebaceous glands, and hair. The cells that are found on the surface of the skin are what make up the horny layer, also known as the stratum corneum. The keratinized dead cells are increasingly abraded due to the regular wear and strain that the skin endures.

Down-growth of tiny, dark, epithelioid cells from the epidermis is a hallmark of all kinds of basal cell carcinoma (BCC). These cells have the cytological properties of cells that reside in the basal layer (BL). These are outgrowths of the basal cells that are found in the epidermis and skin appendages. BCC may be generally classified into differentiated and undifferentiated lesions based on pathological considerations. The differentiation shown in the former lesions is comparable to the differentiation seen in skin appendages, but the differentiation seen in the undifferentiated tumours is absent. The stroma that is present around these downgrowths of dark epithelial cells is the second important component of basal cell carcinoma. It would seem that these two aspects of BCC interact with one another, since efforts to cultivate BCC cells in the absence of stroma have not proven to be effective. Therefore, it would seem that these two components have a mutually beneficial connection with one another. Invasive

melanoma of the skin is characterized by the presence of melanoma cells as well as the fact that the disease spreads into deeper layers of tissue than the dermis. There may be difference in the kind of cells visible in various regions of the tumour, which is referred to as "intra-lesional differentiation." The cells may be of the spindle, epithelioid, or mixed type. There is a possibility that tumour cells, which are free to move about in the dermis, contain melanin pigment in different concentrations.

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2. Literature Survey

A unique image processing algorithms for detecting skin cancer using dermoscopy images are discussed in [1]. The purpose of this study is to examine and favour an algorithm for the detection of skin cancer that can classify the lesions as either malignant or benign melanoma in terms of accuracy, sensitivity, and specificity. This is the motivation for this work. In the beginning, a dermoscope is used to capture image samples that reveal melanoma, and these samples are then segmented. The primary purpose of algorithm in [2] is to present a comparative study on traditional image processing and current technologies of various image processing techniques for skin cancer image classification, preprocessing techniques, feature extraction, and image segmentation datasets.

An strategy for lowering the likelihood of a wrong diagnosis being made is described in [3]. The K-mean Clustering technique is used as the initial step in the data set's preprocessing when following the recommended approach. The removal of any and all extraneous texture is accomplished via the use of this preprocessing, which contributes to an increased pace of reorganization. After the data has been preprocessed, the features may be extracted from it. According to the available research, the most relevant diagnostic factors are the characteristics of the lesion itself, such as its form, color, and structure. In this article, we discuss the many methods now available for the early stage identification of melanoma skin cancer [4].

The categorization of skin lesions is a highly difficult problem, however several automated systems based on various deep learning algorithms have been created so far in order to complete this task. In this particular research project, we classified the skin lesions using three cutting-edge deep learning pre-trained models, such as ResNet, Xception, and DenseNet [5]. The challenge of merging images and metadata characteristics by using deep learning models to the classification of skin cancer is described. Throughout the classification process, we suggest using a new method called the Metadata Processing Block (MetaBlock), which employs metadata to help data categorization by boosting the most important characteristics derived from images [6].

To classify melanocytic skin lesion, a unique technique is employed in [7]. For the purpose of classifying skin lesions such as melanoma, basal cell carcinoma (BCC), seborrhoeic keratosis (SK), and nevus, a support vector machine (SVM) classifier was used. Cancer could be detected at an earlier stage, it would be possible to provide better and more effective therapy. As part of this investigation, a method for the classification of skin cancer is created that is based on a deep convolutional neural network methodology to extract spatial information [8].

A Nevoscope trans-illumination approach for the acquisition of vascular architecture information is described. It then compares the performance of this method to an epiluminescence imaging method for its capacity to measure vascular information for the characterization of skin lesions [9]. Utilizing various image processing methods, the purpose of this research was to identify cases of melanoma skin cancer. Throughout the course of the investigation, a variety of Artificial Neural Network (ANN) models were used, and the classifier performances of each were analyzed [10].

A diagnostic tool for the early detection of breast cancer that has the best possible accuracy and the lowest possible error rate is discussed. This was accomplished by using techniques for machine learning and doing so with the assistance of an Artificial Neural Network (ANN) utilizing the Wisconsin Breast Cancer (Diagnostic) Dataset [11]. An attention-guided approach is discussed in [12]. The purpose of this project is to enhance the performance of these D-CNNs for the categorization of skin cancer. The results of the

classification show that adding attention to a model improves the accuracy of a regular D-CNN architecture. This is something that can be seen. The results of our study provide a substantial contribution to the area of biomedical image processing by delivering a method to enhance the performance of D-CNNs and allowing the early diagnosis of skin cancer.

A computer-based segmentation approach was developed in [13] to give seasoned dermatologists with aid in determining whether or not lesions seen on the skin are cancerous. The goal of this method was to speed up the diagnosis process. The edges of lesions on the original images are drawn by enhancing and segmenting the lesions using techniques that are associated with image processing. This is done because the shapes, colour distributions, and edges of lesions are important parameters in the process of determining whether or not cancer is present. Because of this, the edges of lesions on the original images are drawn. Because of this, the dermatologist will have an easier time studying the lesions and arriving at a conclusion, which will ultimately lead to a decrease in the number of errors that are made.

An autonomously skin cancer classification system has been constructed, and the association of skin cancer images across different kinds of neural networks has been examined using various forms of preprocessing. The system receives the gathered photos, which are then enhanced using a variety of image processing procedures [14]. The detection and classification of melanoma, basal-cell, and squamous-cell skin malignancies are carried out in this study by using a mix of Artificial Neural Networks and the technique of Reinforcement Learning [15]. Different architectures for skin cancer classification and detection are illustrated in [16-18].

3. Proposed System

Texture is a visual pattern that is consistent throughout a surface or an image and is responsible for giving either of those things their unique look. Pixels and texels are both fundamental building blocks of a texture's overall composition. The fundamental components that make up an image's texture are referred to as "texels," which is an abbreviation for "texture elements." A texel is comprised of a certain number of pixels. There is a wide variety of sizes, degrees of homogeneity, and orientations for texels, and they may also be arranged in a probabilistic or structural fashion. "image element" is what "pixel" stands for when it's abbreviated. The arrangement of pixels in a neighbourhood might be random or done in accordance with a particular rule for placement. When a image is captured, the size, rotation, and variations in lighting that are employed all have a role in the viewer's ability to differentiate between different types of textures. The coarse texture is characterized by large sub-regions created by texels, whereas the fine texture is characterized by tiny sub-regions formed by texels. It's possible that low-level or high-level textures were caused by structures included within the dermoscopic images. In many instances, such textures are either caused by disease processes or are impacted by them. The quantification of various surface textures may lead to the discovery of effective disease indicators.

3.1 Texture by spectral analysis

In the case of the Fourier transform, the analysis of signals in terms of their frequency and spatial component is never performed. Wavelet analysis has the ability to overcome these restrictions. Wavelet analysis offers a framework that enables the study of signals in terms of their frequency components on a variety of scales that are both adequate and matched appropriately. When doing wavelet analysis, the first step is to define the mother wavelet. This is the fundamental function, and all subsequent wavelets may be generated from it by moving or distorting the original. The wavelet transform is not the same as the Fourier transform in terms of its basis functions. Unlike the Fourier transform, the wavelet transform has functions that are non-zero on a subset of the domain that is finite, whereas the sine and cosine functions are defined over an indefinite interval and with an infinite set. In contrast to the intrinsic regularity of the Fourier techniques, the effects of this are the subdivision of frequency space according to the frequency of basis functions.

3.2 Decision Tree Classification

When it comes to classify the testing samples, decision tree is one of the most useful classifier available. It has a structure that is similar to a tree, and that structure is represented by three components: internal nodes, branch, and terminal node. A test was performed on either an attribute or a feature when the internal node was present. The branch is used to indicate the results of the test, and the leaf node stores the label for the class. During the training phase, decision tree makes use of a

recursive partitioning technique to divide the source set into many distinct sub-sets. When choosing a split, it is necessary to first evaluate all of the possible divisions and then apply a function known as a splitting criteria to each potential division. The split that achieves the best results in terms of the splitting criteria is selected. After the first step of producing two subsets, these subsets are subsequently divided in order to generate a total of four subsets. This process repeats itself in a cyclical manner. When a pure subset is produced, the dataset does not undergo any additional partitioning beyond that point. When all of the subsets are complete, the partitioning process is finished. If a subset has all of the same values as the target class, then we say that it is pure.

4. Results and Discussions

The PH2 database, which can be obtained for free from the website, is used in the analysis of the proposed skin cancer diagnosis method (Mendonca et al. 2013 [19] and PH2 database link [20]). It consists of two hundred and zero dermoscopic colour images that show melanocytic lesions. Images obtained from a dermoscopy have a resolution of 768 by 560 pixels. For the categorization, there are 80 normal images and 120 abnormal images accessible, of which 80 are benign and 40 are malignant. Samples of normal images from the PH2 database are shown in Figure X.

Table 1 shows the performance of the proposed skin cancer diagnosis system in terms of sensitivity, specificity and accuracy with different number of trees.

It is clear from looking at the Table 1 that the features are classified by the DT-20 classifier provide superior performance than other classifiers with different number of decision trees. The system's top achievements is 98.89% of accuracy as measured by the correct classification of types of cancers.

5. Conclusion

In this paper, the stated aims of building a system that can classify the skin cancer by a non-invasive examination, namely using dermoscopic images, have been realized. The area of study that has garnered an incredible amount of attention is that of computer-aided diagnosis achieved via the processing of images. On the other hand, the required software and hardware are now accessible to purchase at prices that are more affordable, which makes it possible to build new applications for image analysis. The computerized diagnostic systems are designed to do a particular diagnosis and are geared toward achieving a certain objective. The extracted features are considered to be of high quality. In order to establish the capacity of classifying skin cancer, a classification approach in the form of a

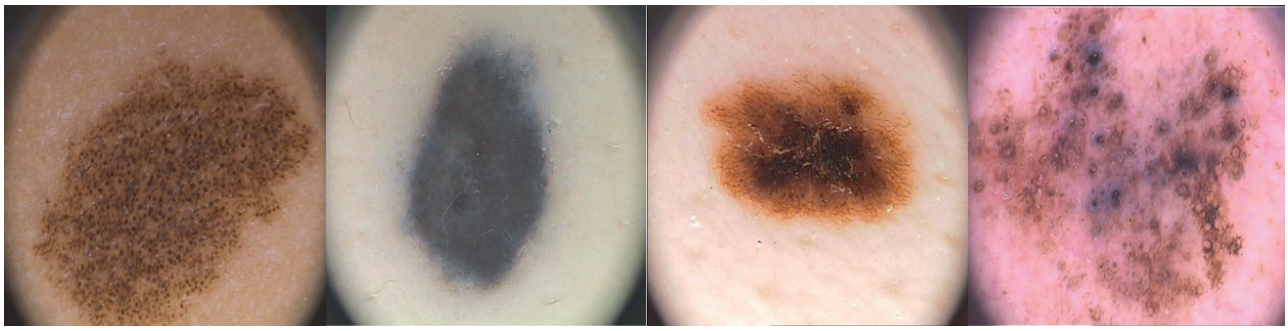

Figure X sample dermoscopic images

Table 1

Performances of the system with different decision tree classifiers

Stages	Performance metrics	Pattern recognizer			
		DT-5	DT-10	DT-15	DT-20
Normal/abnormal	Sensitivity (%)	83.06	86.39	91.39	96.39
	Specificity (%)	90.14	92.64	96.39	98.89
	Accuracy (%)	85.89	88.89	93.39	97.39
Benign/malignant	Sensitivity (%)	86.39	93.89	96.39	98.89
	Specificity (%)	92.64	95.14	97.64	98.89
	Accuracy (%)	90.56	94.72	97.22	98.89

decision tree is utilized. In addition, the performance of the proposed system is evaluated in comparison to the performance of the classification systems configured with different number of decision trees.

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