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ANN-based diagnosis method for skin cancers using dermoscopic images

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Abstract

Melanoma is one of the most dangerous skin cancers in the world. It accounts for 55% of all deaths associated with skin cancer. Researchers believe that skin cancer increases the risk of other cancers if not diagnosed early. Therefore, prompt and timely diagnosis of this disease is very important for the successful treatment of the patient. This system can detect melanoma lethal carcinoma from other skin lesions without the need for surgery, with a low cost, accuracy of about 98.88% and specificity 99%. In this article, a new, intelligent and accurate software (Delphi) system has been used to diagnose melanoma skin cancer. To detect malignant melanoma, the ABCDT rule, asymmetry (A), boundary (B), color (C), diameter (D) and textural variation (T) of the lesion are calculated and finally, an artificial neural network (ANN) is used to obtain an accurate result. The ANN with Multi-Layer Perceptron (MLP) contains the five extraction Characteristics (ABCDT) of lesions is used as inputs, two hidden layers, and two outputs. Very good results were obtained using this method. It was observed that for a dataset of 180 dermoscopic lesion images including 80 malignant melanomas, 20 benign melanomas and 80 nevus lesions. Due to its automatic recognition and ability to be installed on a computer, this system can be very useful for dermatologists as well as the general public.

Keywords: Melanoma skin cancer, ABCDT rule, Feature extraction, Artificial neural network

Introduction

Unfortunately, skin cancer has become very popular these days. Melanoma is caused by genetic mutations in the pigment-producing cells called melanocytes [1]. Melanoma affects mostly both sexes of the Caucasian population [2], and the prognosis of the disease becomes very poor at the metastatic stage [3-4]. There are no effective treatments for metastatic melanoma [5], and has grown rapidly over the past 30 years [6]. According to clinical definitions, malignant lesions are not regularly [6]. Figure **Figure 1** shows the symmetric and asymmetric lesions. Diagnosis of melanoma in the early stages of the disease can certainly prevent the death of patients. Usually for two reasons skin lesions turn from benign to malignant: First, lack of attention to the skin lesions on body surface. Second, high similarity of skin lesions features and inaccessibility to a dermatologist. For example, **Figure 2** shows two very similar skin lesions, malignant melanoma and Clark's nevus, which is a benign skin lesion. Melanoma is the most common skin disease that can lead to death [7], which often begins with malignant pigment cell tumors that cause more than 70% of deaths in patients with skin cancer [8-9]. It should be noted that if skin cancer is not diagnosed in the early stages, it can affect different parts of the body, including the liver, bones, lungs and brain, and makes the treatment process very difficult and complicated. The need for an automatic and accurate device for reduce unnecessary biopsy and rapid detection is quite clear. Therefore, a method for early detection of melanoma is very useful and valuable [10-11] so that dermatologists can use this system to diagnose skin lesions with high accuracy. In fact, melanoma is evaluated by clinical imaging. Dermoscopy is often used to assess melanoma lesions, a non-invasive type of image analysis. A new approach is shown here, which examines the skin lesion image by a trained neural network to analyze if it is benign or malignant. The article is arranged as follows.

Figure 1. A:Symmetric and **B**: Asymmetric melanoma lesions.

Figure 2. Clark nevus.

The second section describes previous work on melanoma analysis in skin images. In the third section, the new contribution to this article describes the analysis, feature extraction, classification, ANN, details, tests and evaluations. Section IV presents the conclusions.

As a basic step towards computer-aided skin cancers, automatic diagnosis, and image analysis have often been studied in the literature [12-19]. In the last few years, many studies have been done to detect melanoma from skin images with an accuracy of 70% to 96%. Telemedicine techniques have been studied as a source for the diagnosis of skin lesions. Compared to physicians in-person diagnoses (face to face) and telemedicine diagnoses (remote detection), tests on skin diseases have shown that the use of tele- communications technology diagnosis (teledermatology) is more effective and safer. These techniques include the benefits of easy access, low cost, and quick and accurate access to treatment results [20-22].

Melanocytic cutaneous lesions have been reported to be the deadliest among the three skin cancer outbreaks and the second most common among adults aged 15 to 29 years [2]. Melanoma is less common in Asia, Africa and Latin America than in Australia, Europe, North America and New Zealand. Melanomas sometimes change in appearance, including changes in size, irregular edges, and discoloration, itching or fracture of the skin [23]. In fact, melanoma can rarely occur in the mouth, intestines, or eyes, but is most commonly found on the skin. It is common in men and women in the back and legs, respectively [24].

The automatic detection of asymmetry in digital images was proposed by the Stolz technique based on ABCD rule [25]. A study on the asymmetry using imaging techniques to identify melanoma skin lesions was presented by Ravichandran et al [26].

To date, many researchers are working on image processing, visual techniques, and various melanoma parameters such as size, shape, asymmetry, border, color, and diameter to detect skin cancer [27-31]. One of the known methods is the ABCD rule. The algorithm for detection is divided into four steps: asymmetry, border, color, and diameter. ABCD is a fast learning, calculation and a reliable way to diagnose melanoma [32-34]. Lesion irregularity, borders, colors and diameters can be analyzed and calculated by dividing the image of the lesion into sub-images and extracting the properties of each image [35]. Finally, melanoma could be detected by a simple threshold for the values obtained from the extracted features (lesion irregularity, borders, colors and diameter) [36]. These features are used as inputs to the first layer of the ANN [37-38].

We've developed the novel ABCDT rule by improve the ABCD, for automatic diagnosis of skin cancer with greater accuracy and precision. In other words, in the current study, the extraction of features is done based on the ABCDT rule in dermoscopy.

Materials and Methods

This article aims to develop a new, intelligent and accurate soft- ware system for skin cancer diagnosis using neural network and ABCDT rule. The input of the device is images of skin lesions. This system with Pre-processing, ABCDT rule, and separation, extract appropriate features from the image. To get the total dermoscopic score (TDS), for each of the "asymmetries, boundary, colors, diameters and texture changes", a coefficient is determined by which the TDS can be calculated.

In other words, to obtain TDS (**Table 1**, the score of each "ABCDT" is multiplied by a specific weight factor. Finally, using NN as a smart medical decision-making system based on TDS, the type of lesion is determined to be melanoma or benign. In other words, an NN has been used to implement the new automated classification of melanocytic lesions.

Table 1. The Proposed diagnostic criteria.

Diagnostic Criteria	Score	Weight Factor
Asymmetric (A)	0-5	1.3
Border (B)	0-8	0.5
Color variation (C)	1-6	1
Diameter (D)	0-1	0.1
Textural variation (T)	1-10	0.9

In this work, briefly, after the detection and elimination of noise and hair on the image, ABCDT rule, Bayes learning algorithm, and the neural network method (Feed Forward Back Propagation) were used to detect the lesion is classified as benign or malignant. AS shown in **Figures 3 and 3**, the architecture of the skin cancer smart system used in this study consists of the five steps of pre-processing, segmentation, feature extraction, classification and diagnosis as follows:

- Pre-processing: It involves filtering and contrast enhancement techniques using the Retinex algorithm. Resize Pictures, to analyze and compare data with the bank, all images are trans- formed into the same size. This size is 450×350 selected.
- Blurring and segmentation: The purpose of blurring is to reduce noise. If we use edge detection algorithms for high-resolution images, we will find many results that we are not interested in. Conversely, if we blur the images too much, we will lose data. So, we have to find the amount of blurring we want to use without destroying the desired edges. There are various techniques to achieve blurred effects, but Gaussian blur is used with a factor of 2 to remove the noise and the hairs on the skin. So, first, the image is converted to binary format. Using filters, detect and eliminate hair and noise from the image. Then, the lesion image is completely separated from the background. In other words, the exact location of the lesion on the image is determined by calculating the threshold and statistical characteristics.
- Feature extraction: ABCDT rule examines the characteristics of a lesion. These properties include asymmetry, border, color, diameter, and textural variation. This rule is a development of the known ABCD rule [39], commonly used to diagnose melanoma from images. The extracted properties are fed to the first layer of the NN.

Properties used to characterize the asymmetry of the lesion

The asymmetric feature of the lesion is one of the important features in diagnosis. Natural moles are usually symmetrical. Asymmetry is usually calculated in two ways: entropy and bifold.

To calculate the asymmetry score, each lesion is examined by two 90-degree axes, and the ANN determines its score. If the lesion is properly symmetrical on both axes, this score is 0, and if it is only on one axis, it will be 2.5. In case of asymmetry in both axes, the score is 5. Finally, the asymmetry score must be multiplied by 1.3 as the weight factor.

Features used for irregular characterization at the lesion border

Uneven or irregularly shaped margins increase the likelihood of some kind of skin lesion. To calculate boundary irregularities, the lesion is divided into eight sections. If the entire border of the lesion has a severe incision, it is given a maximum score. Otherwise the minimum score of 0 is given. The minimum and maximum score of B are defined 0 and 8, respectively with the 0.5 weight factor.

Features used to characterize lesion color variation

Color properties are calculated between six colors, and each color represents 1 point.

Properties used for diameter

According to our information, if the lesion diameter is larger than 0.6 mm, the risk of cancer is higher. Diameter with a weight coefficient of 0.1 is measured by converting the total number of pixels in the largest diameter to millimeters (mm).

Characteristics used to characterize the textural variation of the lesion

Since healthy skin is reddish, and skin lesions have more textural variation and lower pixel intensity than healthy areas of the skin. For this purpose, first, a low pass filter was used to normalize the color and then extracted the correct features [40]. The textural variation values are considered from 1 to 10 with a weight factor of 0.9.

Classification

The different features extracted from the lesion surface have different weights. The weight of each group was drawn based on the experience of dermatologists. **Table 1** shows the importance of each group. The total dermoscopy score (TDS) can be calculated using eq. (1).

$$TDS = 1.3 \times A + 0.5 \times B + 1 \times C + 0.1 \times D + 0.9 \times T \quad (1)$$

Where: A, B, C, D, and T Scores are for the asymmetry feature, the border irregularity, the color feature, the diameter size feature, and the textural variation, respectively.

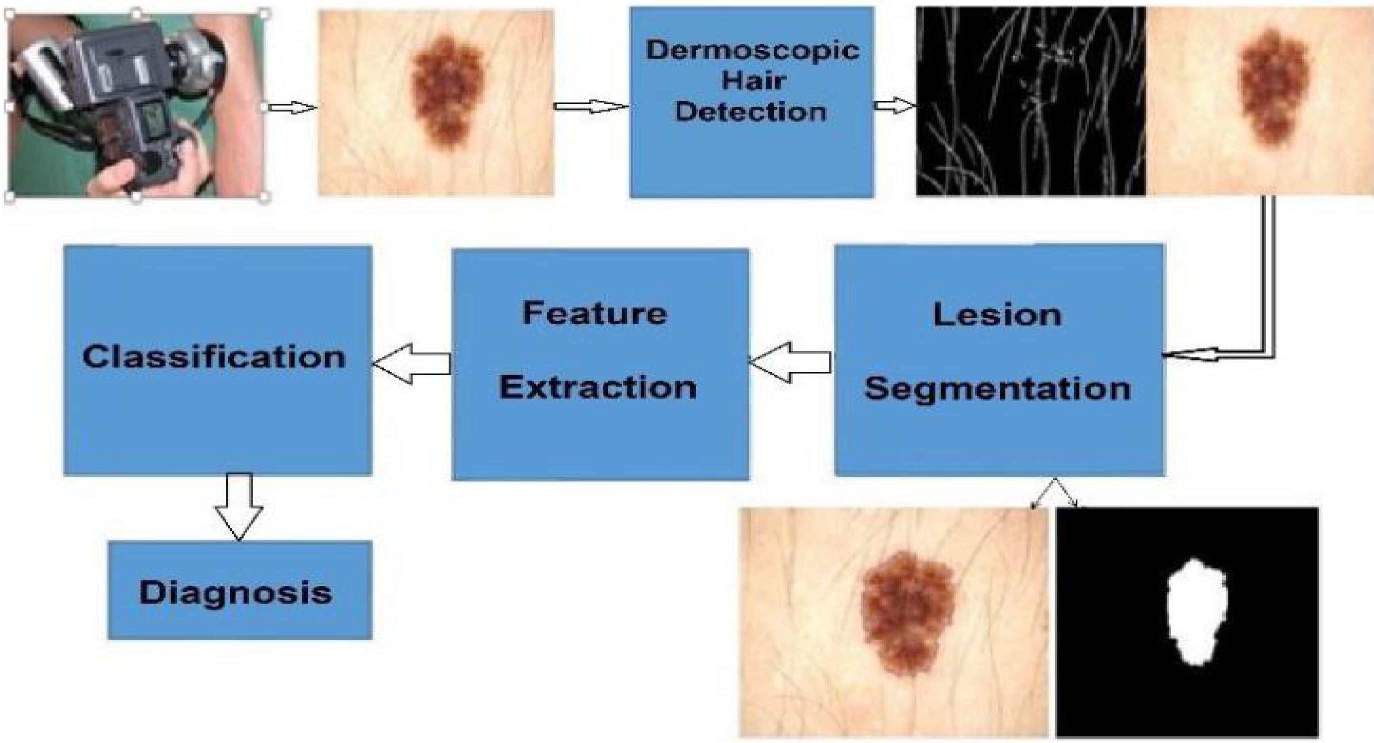

Figure 3. A flowchart illustrating the proposed machine learning system for detecting skin cancers using dermoscopic images.

Figure 4. Clark nevus.

Diagnosis

If individual scores of asymmetry, boundary, color, diameter, and textural variation are multiplied by weight- factor of 1.3, 0.5, 1, 0.1, and 0.9, respectively, a precise distinction can be made between benign and malignant melanocytic lesions. The TDS greater than 5.40 means a cancerous lesion, otherwise, it is benign.

Results and Discussion

All of these steps and the final decision (benign or malignant) are performed by a trained neural network.

Various classifications have been performed by researchers for the ANNs [43-46]. In this work, the ANN with a multi-layer perceptron (MLP) utilizes a supervised learning technique and includes features extracted as inputs to the input layer with two hidden layers containing 10 and 7 neurons for each layer (**Figure 5**). The MLP uses a region-oriented hybrid algorithm, a method called elliptical symmetry to determine asymmetry, a Gaussian smoothing to measure boundary irregularities, and a threshold method for the lesion segment. Therefore, the system designed to diagnose melanoma uses five features of the lesion.

The images used in this work were taken from the international skin imaging collaboration (ISIC) [41]. Out of this dataset, 180 dermoscopic lesion images including 80 malignant mela- nomas, 20 benign melanomas and 80 nevus lesions were ex- tracted and preprocessed for this research.

In several studies [42-44] they used ABCD rule to detect and analyze pictures, whereas in our study we added one more factor (ABCDT) to increase the efficiency and get the better result. We found out The T factor has a huge impact on increasing accuracy.

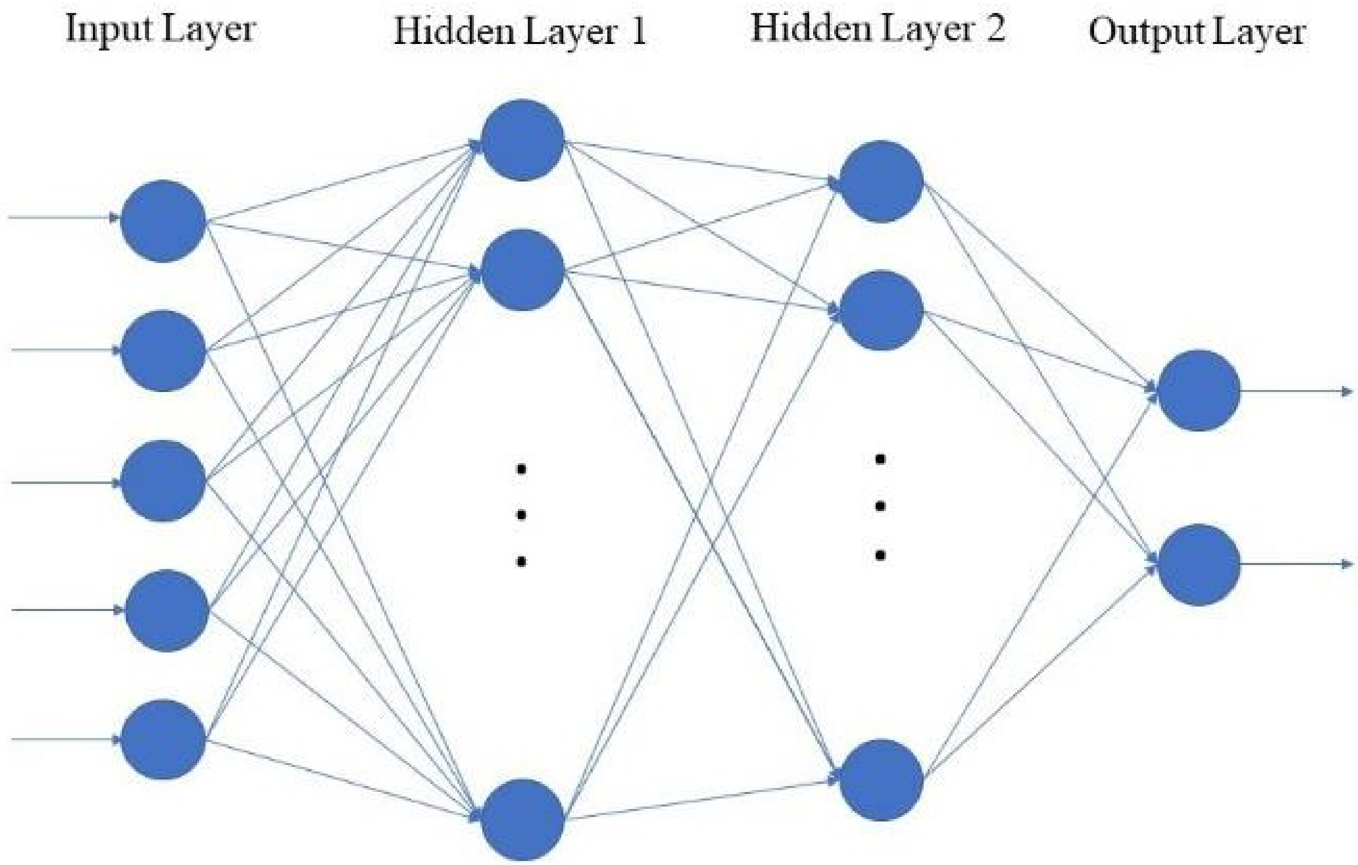

Figure 5. The neural network diagram of the proposed MLP model.

Given the weight factor (0.9) and values of the (0-10) change intended for T, the number obtained from T has a great effect on the result, and this is the most important difference between this work and other similar tasks.

According to the accuracy (ACC) and specificity (SPEC) obtained and compared with Pennisi et al. [47], Fan et al. [48], Jahanifar et al. [49] and Sreelatha et al. [50] can be claimed that the average performance of the technique used in this study is better than previous techniques (**Table 2**).

Table 2. The Average performance evaluation metrics (%).

Algorithm	ACC	SPEC
Pennisi [47]	89.40	97.10
Fan [48]	93.60	-
Jahanifar [49]	97.90	98.20
Sreelatha [50]	98.64	99.22
Proposed MLP	98.88	99.00

The proposed method for the diagnosis of melanoma skin cancer by ABCDT method revealed 98.88% accuracy and specificity 99%. This approach is safe, accessible, effective, non-invasive and based on the principles of telemedicine with high ac- curacy and reasonable price.

With this software system, people can make an early diagnosis of their skin lesions without referring to a physician and specialists can use it as an intelligent, fast and accurate assistant. In summary, the ABCDT rule, Bayes learning algorithm, and neural network method were used to detect the type of carcinogenic or non-cancerous lesions. According to TDS, it is a clear fact that the three features of asymmetry, color, and textural variation of the lesion are crucial in the diagnosis of melanoma from benign lesions. A TDS value above 5.40 indicates melanoma. In ABCDT method, all steps perform by a fully automated neural network.

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