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Classification Models for Skin Tumor Detection Using Texture Analysis in Medical Images

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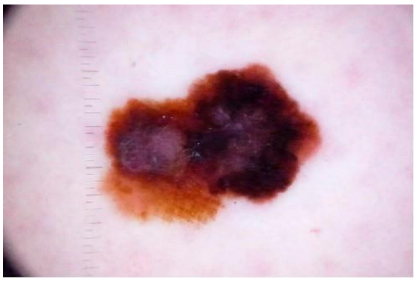
Abstract - Medical images have played a major role in early diagnosis. A new technique for examining diagnostic photographs of skin with melanoma and other cancers is introduced in this report.nevus is used to model, classify, and distinguish skin lesions.Machine learning is used to analyse data produced by the first and second phases.Gray Level Co-occurrence is a function of second order statistics.Color channel knowledge, keypoints, and matrix (GLCM)—Skin representations in red, green, blue, and grayscale were used.to characterise crucial data for the classification ofthe pictures. This paper proposes a method for analysing skin images with the aim of assisting dermatologists in the detection of melanomas, especially early detection, by selecting the best mathematical classifier model for melanoma detection.

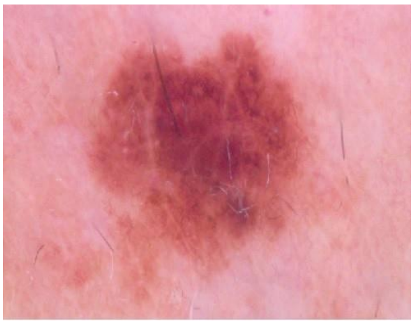
.***Key Words***: texture analysis, melanoma, glcm matrix, machine learning, classifiers.

1. INTRODUCTION

The skin cancer is among the most common types of cancer in the world [1]. Melanoma is the most dangerous type of skin cancer, caused by over production of melanin pigments that change the color and texture of skin, resulting as a dark area on the skin [2]. Data indicate that the incidence of melanoma, which is a type of cancer that metastasizes rapidly, has increased alarmingly [3]. However, visual analysis is limited by human visual ability, as well as human perception and sensitivity, in addition to the fact that not all melanomas have the same characteristics. The tumor is an exceptional expansion of human cells that reproduce in an unrestricted way and that can be identified by a variation of color and texture of the human tissue under study, making information contained in the images extremely valuable. Textures are visual patterns, which have brightness, color, slope, size and other attributes. . When partitioned into sub-images by regions of interest, they are able to be properly classified. Color is one of the significant features in the examination of skin lesion. The distribution of texture and color features presents significant information, as Figure 1 shows.



(a)



(b)

Figure 1. Images of melanoma and nevus tissues: (**a**) Skin lesion from melanoma image; (**b**) Nevus Skin.

A technique of analysis that focuses on the extraction of intrinsic characteristics of the image such as—brightness and color, providing an idea of the roughness or smoothness, among other characteristics, is texture analysis. Digital image texture analysis refers to techniques that use image processing in order to extract representative features of the images studied which can have importance in the discrimination between images. This makes it possible to accelerate decisions concerning diagnosis. In these cases, image quality is essential, relying on bandwidth, sensitivity, resolution and signal-to-noise ratio of the image systems. Artificial intelligence can be very useful in assisting oncologists and radiologists in making early diagnoses of tissue regions with melanoma.

2. RELATED WORKS

Some research works are related to our study because they use convergent techniques for texture analysis.

The diagnosis of skin lesions was studied by Zhang [7]. The analysis considered Convolutional Neural Networks (CNN) for automatic detection of skin cancer, comparing this with other research methods. The proposed

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method called CNN/WOA achieved an accuracy of 91.00%, with a sensitivity of 95.00% and specificity of 91.00%.

Pathan [8] reviewed the cutting-edge techniques declared in the literature, summarizing these state of art approaches. The steps included dermoscopic image pre-processing, segmentation, extraction and selection of peculiar characteristics and disposition of the skin lesions. The study also evaluated the consequences of the methodologies reported in the literature in addition to the results and future directions of research. The best result from the listed methods and algorithms was the Otsu threshold with Active Contour using a Sparse-Field level-set method, with a precision ability of 97.50% for the detection of melanomas.

Lee et al. [9] proposed the skin disease classification solution using Fine-tuned Neural Networks. The model achieved an accuracy of 89.90% and 78.50% in the validation set and the test set, respectively.

3. MATERIALS AND METHODS

There follows a general description of the statistical parameters used in the proposal of this work, for the extraction of characteristics from the images. These characteristics make up the co-occurrence matrix (GLCM) and are part of the keypoints, applied to each image. Let f (x, y) be a function of two discrete variables x and y, $x = 0, 1, \ldots, N - 1$ and $y = 0, 1, \ldots, M - 1$. The discrete function f (x, y) can assume values for $i = 0, 1, \ldots, L - 1$, where L is the number of grayscale levels. The intensity-level histogram is a function showing (for each intensity level) the number of pixels in the whole image, which have this intensity:

$$h(i) = N\ X-1\ x=0\ M\ X-1\ y=0\ \delta(f(x, y), j)$$

(1) where $\delta(i, j)$ is the Kronecker delta function
(2) The probability of occurrence of each pixel in the image that will appear in the histogram is given by:

$$p(i) = h(i) / M ,\ i = 0, 1, \ldots, L - 1$$

Haralick [20] proposed a set of scalar quantities for summarizing the information contained in a GLCM.

Originally these comprised a total of 14 features namely, angular second moment, contrast, correlation, sum of variance, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation and maximal correlation coefficient. In order to obtain texture features, the normalized GLCM was computed for each of four orientations (0◦ , 45◦ , 90◦ and 135◦). GLCM expresses the texture feature according to the calculation of the conditional probability of the pixel pair of the gray intensities, for the different spatial positions.

$$p(i,j \mid d,\theta)=p(i,j,d,\theta)/EiEjp(i,j \mid d, \theta) .$$

The next step was to format a proposal, containing the extraction of characteristics from medical images to build a classification based on several state-of-the-art classifiers.

4. PROPOSED STRATEGY

The present study investigates the best strategy for aiding in the diagnosis of the presence or absence of melanoma through skin imaging. In the proposed strategy, what differentiates it from other methods of texture analysis is the inclusion of RGB components, adding texture information to the keypoints.

The developed strategy involves the following steps:

1. Random selection of a set of images with melanoma and nevus.
2. Generation of keypoints containing:
   a. first order statistics information;
   b. second order statistics parameters;
   c. RGB component information.
3. Extraction of characteristics from all training images.
4. Classification phase with the modeling using the training database.
5. Application of the selected model to a test image database.
6. Result of the model applied to the test database.

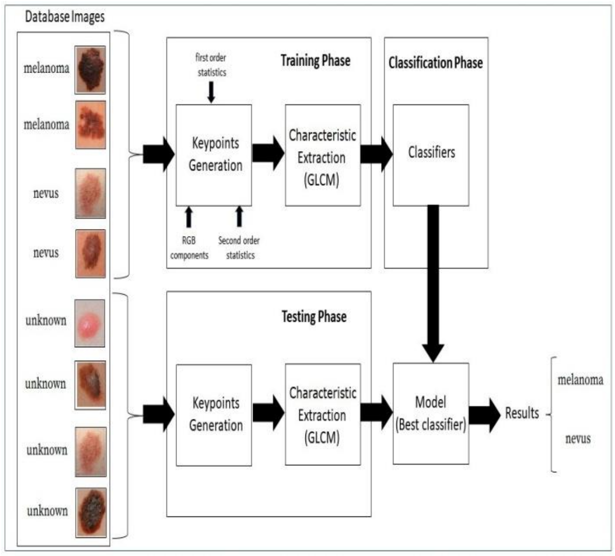

Figure 2. Block Diagram of the proposed strategy.

All data sets used are available in the Skin Lesion Analysis Towards Melanoma—International Skin Imaging Collaboration (ISIC) 2019 [25].

The database was formed by 2000 jpeg skin images, selected at random. The learning process was performed on 75% of the database, as in this research, 10 samples were used per image, the learning process analyzed a total of 15,000 samples. In the testing process, the remaining 25% of the images in the database were used, making a total of 5000 samples in the testing phase. Each sample had a dimension of 6 pixels × 6 pixels.

To increase the effciency in extracting characteristics for diffrentiation of the tissues, it was necessary to add parameters as first and second order statistics into keypoints, such as—mean, variance, kurtosis, skewness, contrast, correlation, entropy, energy, maximum and minimum value, as well as RGB components.

In machine learning, the classification identifies to which Class a set of observed data belongs.

Classification is an example of pattern recognition. Some variants of the classifiers cited and available in the library of the Python environment were used, to increase the set of classifiers tested:

1.sklearn.linear_model.SGDClassifier;

2.sklearn.naive_bayes.GaussianNB;

3.sklearn.naive_bayes.BernoulliNB;

4.sklearn.naive_bayes.MultinomialNB;

5.sklearn.tree.DecisionTreeClassifier;

6.sklearn.ensemble.ExtraTreesClassifier;

7.sklearn.ensemble.RandomForestClassifier;

8.sklearn.ensemble.GradientBoostingClassifier;

9.sklearn.neighbors.KNeighborsClassifier;

10.sklearn.svm.LinearSVC

After the computational effort using the twelve classifiers, the five best ones were selected, based on the area under the Receiver Operating Characteristics:

1. Linear Model Logistic Regression.
2. Gradient Boosting (Stochastic Gradient Boosting).
3. SVM Linear SVC (Support Vector Machine Linear—Support Vector Classification).
4. Linear Model Stochastic Gradient Descendent (Linear Model SGD).
5. SVM SVC (Support Vector Machine—Support Vector Clustering).

The results of the database simulation are provided in detail in the following sections

5. RESULTS

First-order statistics concern the distribution of gray levels in an image, where the first-order histogram is used as the basis for extracting its characteristics, such as—mean, standard deviation, kurtosis and skewness, as shown in Table1. These are not sufficient, however, for decision making between what is melanoma tissue and what is healthy tissue. The Mann-Whitney U test applied to the parameters show that ($p < 0.05$), therefore, the null hypothesis is rejected. Meaning that the distributions of both samples (melanoma and nevus) are not the same.

The confusion matrix of the Logistic Regression method that describes the complete performance of the model is shown in Figure 3. This generates a sensitivity and specificity of 0.97.

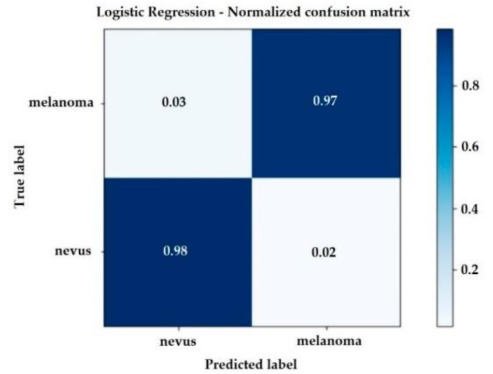

Figure 3. Confusion Matrix considering the Logistic Regression Model.

For the best performance model, the probability curve is shown through the sigmoid curve showed in Figure 4.

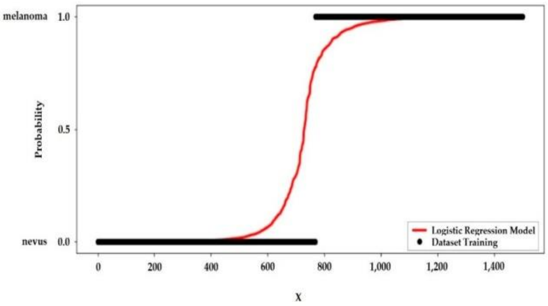

Figure 4. Logistic Regression Model of the Proposed Strategy.

The specificity is 15.99%. The number of positive and negative outcomes change as we change the threshold of probability values to classify a probability value as a positive or negative outcome. Thus, the Sensitivity and Specificity will change as well.

6. DISCUSSION

Although the results were satisfactory with the use of statistical techniques, for future studies, it should be noted that when second order GLCM parameters were used, it is necessary to take some precautions regarding the size of the region of interest.

considering the test database, reached levels between 95.04% and 97.46%, which corresponds to an accuracy between 95.00% and 97.00%, respectively. The Linear Model Logistic Regression classifiers were the most accurate.

This shows the effectiveness of second-order statistics and the inclusion of RGB components in the composition of keypoints in improving performance of the proposed strategy.

7. CONCLUSIONS

The proposed mechanism of identifying and classifying skin tissue is general; in future work it can be applied to other medical images to verify the results, since the strategy analyzes the texture of the images and reveals their differences according to the parameters set, enabling the image classification. Texture analysis utilizes the changes in the grey value of image pixels and their distribution pattern, which can reflect microscopic pathological changes that are not visible to the human eye and can be used in the analysis of various images. Thus, texture analysis in medical imaging can be a substantial support for the clinical decision-making process in the diagnosis and classification of tumors. This methodology is expected to become more accurate than the human eye in detecting minute deviations in cell and tissue structures. Statistical methods using GLCM features, associated with red, green and blue color information to perform micro-texture analyzes of human tissues and image classification for tumor detection showed great efficiency in the results presented. The results show that for the detection of melanoma in human tissues, the logistic regression model was the best model with 97.00% of accuracy and precision on benchmark dataset and also a sensitivity and specificity of 97.00%. The second-best method of classifying the data of the evaluated medical images was the Classification of the Gradient Boosting

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Conflicts of Interest: The authors declare no conflict of interest.

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