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AN OVERVIEW OF CLASSIFICATION METHODS FROM DERMOSCOPY IMAGES IN SKIN LESION DIAGNOSTIC

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Abstract. *The article contains a review of selected classification methods of dermatoscopic images with human skin lesions, taking into account various stages of dermatological disease. The described algorithms are widely used in the diagnosis of skin lesions, such as artificial neural networks (CNN, DCNN), random forests, SVM, kNN classifier, AdaBoost MC and their modifications. The effectiveness, specificity and accuracy of classifications based on the same data sets were also compared and analyzed.*

Keywords: dermatoscopic images, classification methods, neural networks, SVM, skin cancer, skin lesions

PRZEGLĄD METOD KLASYFIKACJI OBRAZÓW DERMATOSKOPOWYCH WYKORZYSTYWANYCH W DIAGNOSTYCE ZMIAN SKÓRNYCH

Streszczenie. *Artykuł zawiera przegląd wybranych metod klasyfikacji obrazów dermatoskopowych zmian skórnych człowieka z uwzględnieniem różnych etapów choroby dermatologicznej. Opisane algorytmy są szeroko wykorzystywane w diagnostyce zmian skórnych, takie jak sztuczne sieci neuronowe (CNN, DCNN), random forests, SVM, klasyfikator kNN, AdaBoost MC i ich modyfikacje. Porównana i przeanalizowana została również skuteczność, specyficznośc i dokładność klasyfikatów w oparciu o te same zestawy danych.*

Słowa kluczowe: obrazy dermatoskopowe, metody klasyfikacji, sztuczne sieci neuronowe, SVM, nowotwór skóry, zmiany skórne

Introduction

Nowadays, the classical classification methods of dermatoscopic images used by generations of doctors are becoming insufficient. These include the ABCD, Hunter, Menzies method [25], 7-point checklist [4], TDS, Chaos-Clue [29], scale Glasgow, scale Hunter and many others [3, 7, 22]. They do not allow to effectively diagnose cancer and save human health and even life [5].

Classic pattern analysis gives the opportunity to describe skin lesions for diagnostic purposes, five basic elements are enough: lines, circles, pseudopodia, papules and dots. Each of these elements can be part of the pattern. To create a pattern, it is necessary to repeat the same structure multiple times. The presence of specific colors and the number of colors is of great importance in dermatoscopy. The Hunter scale gives a score in the range of zero to thirteen points. Clinical symptoms suggesting suspected melanoma are often grouped in two systems: the ABCD scale and the seven-point Glasgow scale. Chaos – Clue is a simple method for quickly assessing suspected pigmented skin lesions with a dermatoscopy. Its use can lead to a better diagnosis of melanoma and other skin cancers [29]. Figure 1 presents the most important stages of this algorithm.

Therefore, automated diagnostic systems have been developed to assist doctors in the diagnostic process. The images used in programs are subjected to the process of removing artifacts, segmentation of changes, extraction of features, optimization and finally classification of the skin lesions. Most often, the lesions is characterized by the type of damage, color, arrangement, shape, texture and border irregularity. Currently, the classification of skin lesions uses automatic recognition of lesions or known anomalies occurring in a given population. These methods are also intended to classify a given birthmark as a pattern with a colored texture.

Classification means that elements of set $X = \{fx_1, x_2, \ldots, x_n\}$ are assigned elements of set $Y = \{fy_1, y_2, \ldots, y_n\}$, for $i = 1, \ldots, n$, where n is a number of objects. The set X is called the set of feature vectors x_i, but Y is a set of classes y_i. The classifier construction process consists of preparation of learning data, test subset, classification and calculation of classification efficiency.

One of the first ways to classify was discriminant analysis [18]. Next appeared artificial neural networks (ANNs) [14, 20], decision trees [21], support vector machine (SVM) [11, 12], logistic regression [8], ensemble learners [2, 30]. Many different classifiers have been used to classify dermatoscopic skin images. Skin melanoma is classified using kNN classifier [9]. The AdaBoost MC algorithm [1] is considered optimal and reliable.

The types of machine learning algorithms are commonly divided into 4 categories: supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. The mostly common supervised learning algorithms are nearest neighbor, naive Bayes, decision trees, linear regression, logistic regression, linear discriminant analysis, SVM, neural networks, similarity learning. Algorithms try to model relationships and dependencies between the target prediction output and the input features. They predict the output values for new data based on those relationships which it learned from the previous data sets.

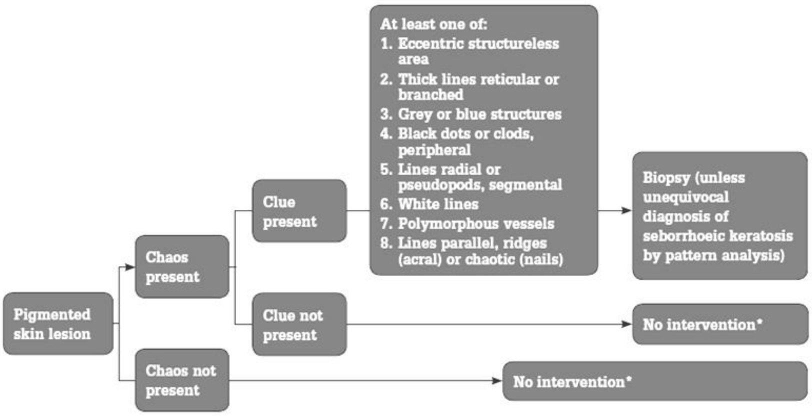

Fig. 1. Algorytm działania metody Chaos – Clue [29]

The most current methods in the field of melanoma classification use artificial neural networks of increasingly complex structure. The most commonly used include artificial neural networks, logistic regression, decision making using trees and supervised machine learning algorithms.

1. Supervised machine learning algorithm in classification

Support Vector Machines (SVM) is supervised learning model with associated learning algorithm. SVM is most commonly used in classification problems [27, 31]. In the algorithm, each data element is a point in n-dimensional space (where n is the number of features), the value of each feature is a coordinate value. Then elements classification is performed by finding the hyperplane, which differentiates on the best way two classes. The optimal separating hyperplane (OSH) is a hyperplane which margins are the largest.

In [31] the proposed classification model uses HSV, LBP and HOG functions, that are passed to the SVM classifier. The function extraction process has been divided into three parts, features of color, texture and shape of melanoma. Then the feature vector of all these three features was joined to obtain a complex feature vector. The process is repeated for all images in the data set and vector features are marked according to their accepted classes. The labeled feature vectors are fed to the SVM classifier to effectively train the algorithm. In tests, all functions are extracted from the new image and the feature vector is fed to SVM to predict classes. The scheme of described activities is presented in Figure 2.

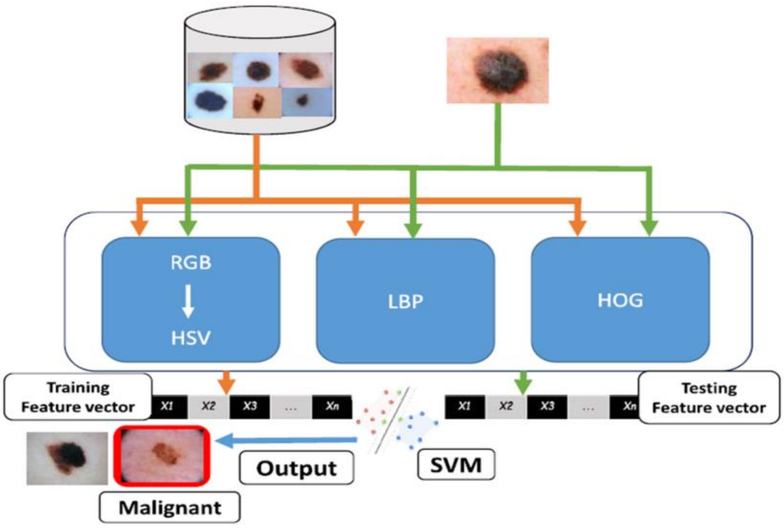

Fig. 2. Diagram of activities using SVM in the classification of dermatoscopic images [31]

2. Classifiers based on Convolutional Neural Network (CNN)

Neural networks are used in many fields of computer science, especially in image processing. Nowadays, various modifications are becoming more and more common. They are used to classify images [15, 17, 23, 31, 33].

More and more scientists are comparing skin diseases diagnostics effectiveness of computer algorithms with experienced doctors. Classification of skin lesions enabling identification of the most common tumors using CNN was used in [16]. The network was trained directly from a data set containing over 129,000 clinical images, using only pixels and skin disease labels as input.

The effects have been compared with the diagnoses of over 20 dermatologists. The doctor's diagnoses were confirmed by an additional skin lesion biopsy. The diagnosed cases were malignant melanomas and benign skin birthmarks. CNN achieves performance comparable to that of expert dermatologists, 22 and 21 experienced doctors participated in the study. Figure 2 demonstrates artificial intelligence possibilities in classification of skin cancer comparable to dermatologists. The charts include results of physician diagnostics and algorithm for 130 melanoma images and 111 dermatoscopic images. The average of dermatologists was also included. It turns out that when diagnosing melanoma, doctors have comparable diagnostic effectiveness to the proposed algorithm. In contrast, their diagnostic ability decreases for dermal pictures containing various stages of skin diseases.

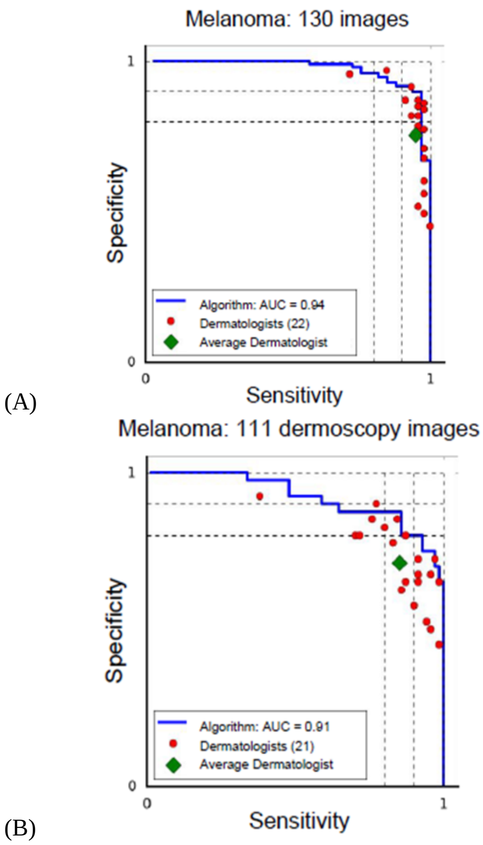

Fig. 3. ROI curves for CNN algorithm and dermatologist: (A) data with 130 images of melanoma, (B) date with 111 images of melanoma [16]

3. Classifiers based on Deep Convolutional Neural Networks (DCNN)

Neural networks different models modifications are increasingly common. They contain deep learning algorithms [13], deep convolutional neural networks (VGGNet convolutional neural network architecture and the transfer learning paradigm) [28], synergic deep learning (SDL). They show great effectiveness in the diagnosis of skin lesions.

In [34] was proposed a model combining synergistic models (SDL) and (DCNN). The proposed model (Figure 4) consists of three modules: an input layer, double DCNN-A/B components and synergistic network. The input layer takes a few images as input. Each DCNN component is for self-study under the supervision of class labels. The synergistic network checks if the pair of input images belongs to the same category and provides feedback.

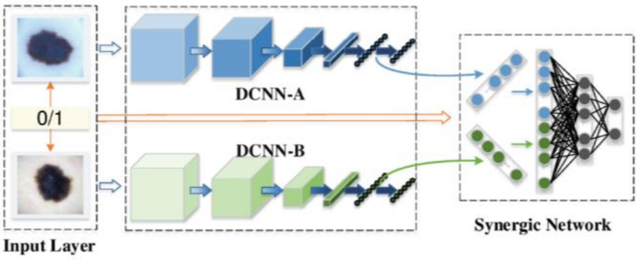

Fig. 4. Proposed model architecture of constructed input layer, double DCNN components (DCNN-A/B) and synergic network [34]

4. Effectiveness of selected classification methods

Many scientists [6, 10, 19, 24, 26, 32] test the effectiveness of available or modified classifiers on various dermatoscopic data. For they research, scientits use a large number of dermatoscopic images using many new modifiers of classifiers.

Figure 5 presents ROC curves (Receiver Operationg Characteristic), which are the tool for joint assessment of the classifier, its sensitivity and specificity. It included AdaBoost MC, ML - SVM, ML - KNN algorithms. The larger area under the ROC curve usually allows for more accurate classification of objects.

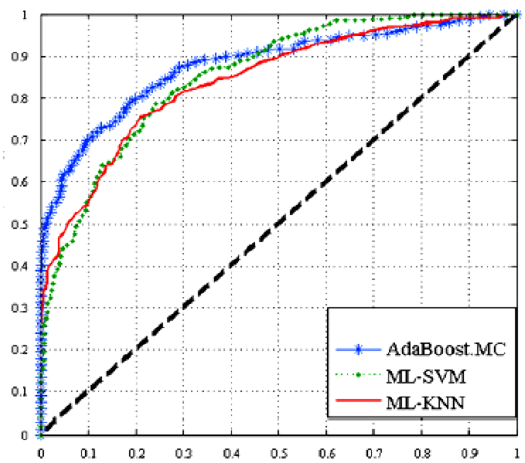

Fig. 5. ROC curves for AdaBoost MC, ML- SVM, ML- KNN algorithms [1]

It is important that the classification algorithms are tested on the same data sets. For this reason, many publications are cited that use different data sets to compare the classifier. Table 1 compares the classifications based on the two models Caucasians (1) and Xanthou (2). Random forests and KNN algorithms showed a specificity above 96%.

Table 1. Results of classifiers based on different models [32]

Classifiers	Sensitivity (%)		Specificity (%)		Accuracy (%)	
	1	2	1	2	1	2
Random forests	73.33	80.00	95.83	**96.25**	88.33	90.83
KNN	51.67	77.50	**97.50**	**96.25**	82.22	90.00
Adaboost	71.67	80.00	95.83	92.50	87.78	88.33
RBF SVM	75.00	87.50	94.17	93.50	87.78	91.67
S – SVM	75.00	85.00	93.33	91.25	87.22	89.17
DCNN	83.33	95.00	95.00	93.75	91.11	94.17

At dermatoscopic images are many artifacts, is not easy to use effective classification algorithm. In [1] pattern based on CASH is very accurate. Skin lesions were classified by pattern detectors classes such as reticular, globural, homogeneous, parallel, cobblestone, starbust, multicomponent. Table 2 presents sensitivity, specificity, accuracy, average standard deviation training error (E) during learning by AdaBoost.MC. Reticular and globural patern detectors have reached a specificity value above 97% for the dermatoscopic image dataset chosen by scientists.

Table 2. Pattern classification of dermatoscopic lessions made by AdaBoost.MC [1]

Patern detector	Sensitivity (%)	Specificity (%)	E	Accuracy (%)
reticular	87.11	**97.96**	0.459	0.981
globural	86.25	**97.21**	0.477	0.997
cobblestone	87.76	93.23	0.555	0.990
homogeneous	90.47	95.10	0.697	0.996
parallel	85.25	89.50	0.524	0.989
starbust	89.62	90.14	0.634	0.966
multicomponent	98.50	93.11	0.344	0.989

In [23] SVM has been compared with the Random algorithm classifier. The best accuracy of class recognition on the database has been achieved in the SVM classifier. SVM associated with attriutes selected by the Fisher method. Scientists have received total accuracy equal to 93.8 % for recognizing melanoma from the other lesions of human skin, sensitivity in recognition of melanoma is equal to 95.2 % and specificity 92.4 %.

5. Discussion and conclusions

In experiments, verification of extraction, reduction of features, classification, performance was tested using various classifiers. These methods are tested on various data sets from around the world. Experimental results strongly suggest that the proposed classifiers are particularly beneficial in distinguishing between malignant and benign lesions. Any classification problem can be solved with more than one classifier. It is important that they are not hypersensitive to damage lesions, eliminate less important functions, reduce the dimension of the function and choose the optimal set.

An effective algorithm should well minimize the object classification error presented in the image. However, the error cannot be completely eliminated. Image elements or the entire image is classified based on a finite set of its features. To improve classification efficiency, it is important to combine available methods.

Equipped with software with classifiers, mobile devices can potentially extend the scope of diagnosis. It is anticipated that many new algorithms will be created in the future. It is important to provide universal access to the necessary diagnostic care. The classification results provided by the tested models over the years prove to be more accurate in the process of diagnosis of skin lesions.

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