

Dermatoscopy software tool for *in vivo* automatic malignant lesions detection

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Abstract. Dermatoscopy is one of the most popular non-invasive methods of skin tumors diagnostics. Digital dermatoscopy allows one to perform automatic data processing and lesions classification that significantly increases diagnostics accuracy compared to general physicians. In this article, we propose a dermatoscopy tool equipped software automatic classifier of dermatoscopic data. Noise reduction and image histogram equalization were performed during the initial step of preprocessing. After this step, a feature-detection step was performed; the program finds region of interest and calculates Haar transform, linear binary patterns, and color-texture features in different color spaces (RGB, HSV and LAB) for both tumor and healthy skin areas. Finally, evaluated features are used for classification by using Support Vector Machines (SVM). This classifier has been trained and tested using 160 dermatoscopic images made with polarized backscattered light. The article shows data for two classes separation: malignant melanoma versus non-melanoma tumors and malignant versus benign lesions. Proposed approach has achieved sensitivity of 83% and specificity of 65% for melanoma versus non-melanoma classification and sensitivity of 61% and specificity of 60% for malignant versus benign lesion classification. Performed cross-validation ensures stability of the classifier. © 2018 Journal of Biomedical Photonics & Engineering.

Keywords: Classification; algorithm; cross-validation; image processing; dermatoscopy device.

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1 Introduction

In Russia in 2016, according to the overall statistics, skin has become the most frequent organ for malignant tumors allocation (14.2% out of all lesions, including 12.5% non-melanoma types) [1]. The most widespread tumor types include basal-cell carcinoma, squamous-cell carcinoma and malignant melanoma [2]. The key factor for better patients survivability consisted in early diagnostics, however, less than one third only of all tumors were diagnosed at the first stage in 2016 in Russia [1]. For this reason, there is a necessity to develop better diagnostic techniques or improve existing ones.

There are a number of different skin diagnostics methods exist. These methods have different nature and provide result of different effectiveness. For example, the sensitivity of a primary naked-eye examination by a general practitioner varies from 25 to 60% for a first time diagnosed melanoma [3]. This is the simplest diagnostics method, which does not require any equipment. Such examination is mandatory now, its accuracy is not high enough and, therefore, it is frequently complemented by instrumental methods.

A group of optical methods should be emphasized among the all instrumental methods. These techniques provide promising results in oncology, especially if

several methods have been used together [4]. Dermatoscopy is one of the simplest instrumental diagnostics methods and it may allow one to increase diagnostics accuracy significantly. Dermatoscopy relies on epidermis imaging with optical magnification followed by features analysis of pigmented lesions [3]. In the simplest case, dermatoscopy is performing visually by an oncologist, but a specialized program may be integrated into a dermatoscopy tool to evaluate necessary features [5, 6].

Dermatoscopy with ABCD analysis increases diagnostics sensitivity up to 78.4% and specificity up to 79.6% in melanoma vs non-melanoma case for trained physicians. Other analysis methods, such 7-point checklist, provide sensitivity up to 100% and specificity up to 69.8% in the same conditions [7]. One of the most successful results of automatic classification has been achieved by A. Esteva et al. [8]. They have achieved overall accuracy of 72.1% using Convolutional Neural Network (CNN) for three-way classification of benign, malignant and non-neoplastic lesions.

Other optical methods, such as confocal microscopy, Raman spectroscopy, hyperspectral and fluorescence diagnostics, optical coherent tomography (OCT) shows diagnostics accuracy of more than 80%. However, all of them share disadvantages of high cost and relative hardware complexity. Hyperspectral diagnostics allows one to analyze both morphological and spectral features of skin surface. Results of hyperspectral imaging diagnostics heavily depend on data processing methods, but many researchers report accuracy of malignant vs benign lesion classification to be more than 80% for melanoma detection [4, 9, 10]. Methods based on fluorescence diagnostics [11] and OCT [9, 12, 13] also show 80-90% accuracy for basal-cell carcinoma detection. Confocal microscopy [14, 15] and Raman spectroscopy [9, 11, 16] could result in more than 90% accuracy for various types of lesions detection, such as basal-cell carcinoma and malignant melanoma.

In addition, there are number of non-optical diagnostics methods, such as ultrasound or thermal imaging. Thermal imaging method is based on temperature difference between malignant and benign lesions. V. Anisimov [4] mentioned sensitivity of 90.5% and specificity of 80.2%. However, melanoma detection on early stages with dynamic thermal imaging is almost impossible [17] due to more significant temperature dependence on the blood flow. Thermal imaging diagnostics accuracy also depends on a lesion thickness [18].

Ultrasound methods allow one to determine local melanoma distribution, but thickness measurements could give erroneous results in some cases [3]. Melanoma versus nevi classification based on ultrasound data and using Support Vector Machines (SVM) classifier shows sensitivity of 85.8% and specificity of 79.6% [19].

The aim of this research is developing a dermatoscopy diagnostic tool with additional software SVM classifier. The tool allows us to control all

possible image acquisition parameters and makes it possible to eliminate any unwanted processing steps, which could unexpectedly influence classification algorithm. A prototype of the dermatoscopic tool and the software have been created. Clinical dermatoscopic examinations were also conducted and dermatoscopic data classification accuracy was estimated.

2 Materials and methods

2.1 Tool design

An optical design of the dermatoscopic tool prototype is presented in Fig. 1. This tool is based on a BASLER Ace 1920-25uc color camera. The camera produces 1920×1080 pixel images representing a Bayer (GB) mosaic for a 25×14 mm field of view on the surface of the skin. RGB images are constructed from the mosaic using linear interpolation. In terms of frame acquisition timing control, this camera has a rolling shutter, but a global reset release shutter mode has been enabled. Backlight LEDs are synchronized with the shutter in such a way that LEDs emit light only when all lines of the sensor are exposed. This shutter mode coupled with backlight synchronization effectively creates a global shutter effect in terms of input light. Integration time could be set independently for each type of backlight while all the other types of automatic acquisition control (i.e. gain, gamma, white balance corrections) are switched off.

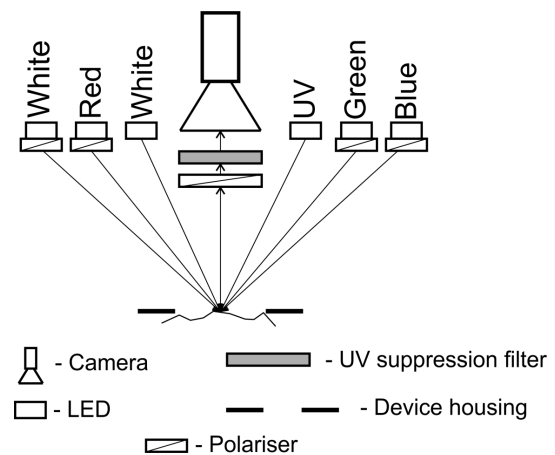


Fig. 1 Optical diagram of the dermatoscopic tool prototype.

Device uses several LEDs to illuminate skin area: 4 white LEDs FM-5630WDS-460W-R80 (2 of them are covered with a polarizer to visualize deeper skin layers); UV range LEDs LEUVA77V20RV00 (365nm) for skin autofluorescence analysis; three types of visible light LEDs CREE XPCReD-L1-0000-00301, CREE XRCGRN-L1-0000-00N01 and CREE XREBLU-L1-0000-00K01 to visualize skin in red (620nm peak), green (530nm peak) and blue (470nm peak) ranges respectively. For further 365nm excited autofluorescence analysis the radiation is filtered with

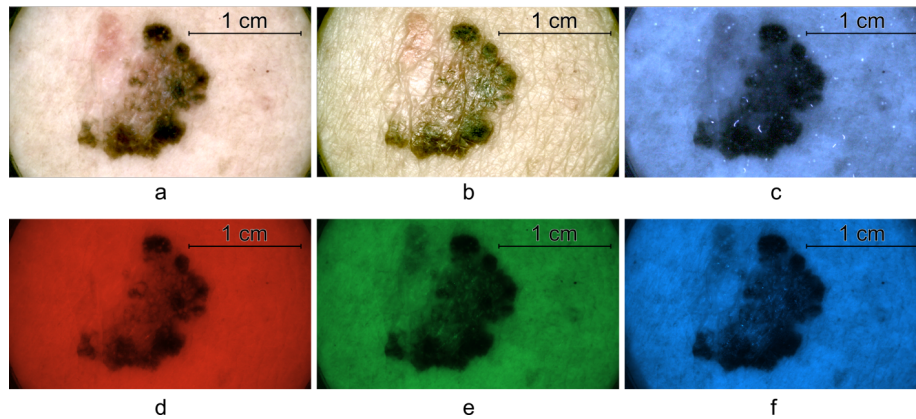


Fig. 2 Images made using different backscattered light (a-f): (a) White polarized light; (b) White non-polarized light; (c) Autofluorescence; (d) Red light; (e) Green light; (f) Blue light.

ThorLabs FGL435 (435nm) long-pass filter, which is always installed on the lens and non-removable for a user. All LEDs are switched in sequence synchronized with camera's frame acquisition. The current switching sequence is the following: polarized white light, not polarized white light, red light, green light, blue light and an ultraviolet autofluorescence.

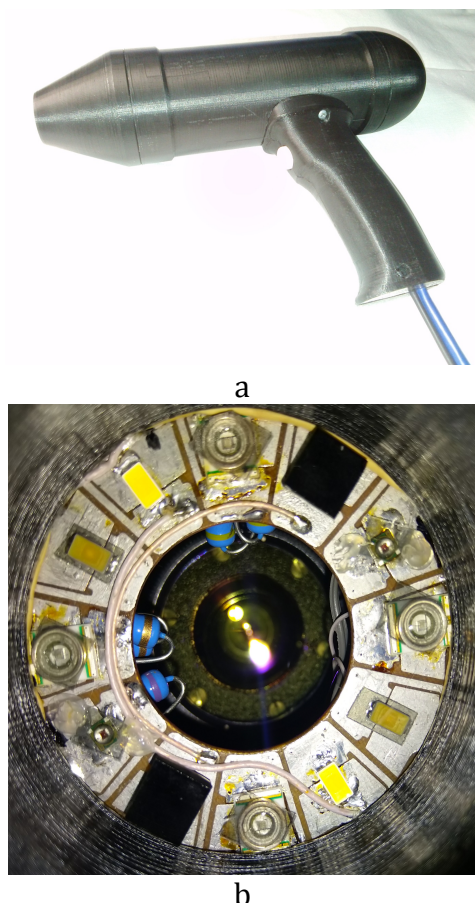


Fig. 3 The tool prototype used for data gathering. (a) General view of the designed dermatoscopy tool; (b) tool lighting ring and a camera lens.

The UV diode outputs up to 1W inside of 110° solid angle. Considering its placement at a distance of 75 mm from the device's window, the patient's skin UV exposure is 130J/m^2 for 1sec typical acquisition time that does not exceed ANSI maximum permissible exposure. All visible light LEDs output from 40 to 100Lm, which results in less than a 1J/m^2 exposure for a typical acquisition time of 0.1sec.

Linear polarization is used to filter out light directly reflected from skin surface, as it is necessary for deeper epidermis structure visualization and for light absorption estimation at different wavelengths in visible range. Linear polarization filter "ПФ-3" has been installed in the device. Examples of skin images obtained by the described above tool are presented in Fig. 2, the tool prototype itself is presented in Fig. 3a, while Fig. 3b shows the device backlighting LEDs ring. It could be noted that there are two LEDs of each type to provide more uniform backlight. A polarizing film is used for LEDs light polarization, while the ПФ-3 filter and a long-pass filter are installed permanently on the camera lens. The lens itself is placed behind the lighting ring looking down on a skin through the hole in the middle of it.

2.2 Automatic lesion detection

A proposed algorithm classifies tumors by using color and texture features evaluated from images with polarized white backlight (the closest approach to a usual dermatoscopy). Majority of this algorithm's steps were described in details in Ref. [20], but we are going to mention it here again in regard of this particular implementation for better representation of the whole system.

The algorithm (Fig. 4) consists of the following steps:

- 1) initial image processing;
- 2) region of interest (ROI) detection;
- 3) calculation of color and texture features;
- 4) SVM classifier training or using the pre-trained classifier to get the final diagnostic

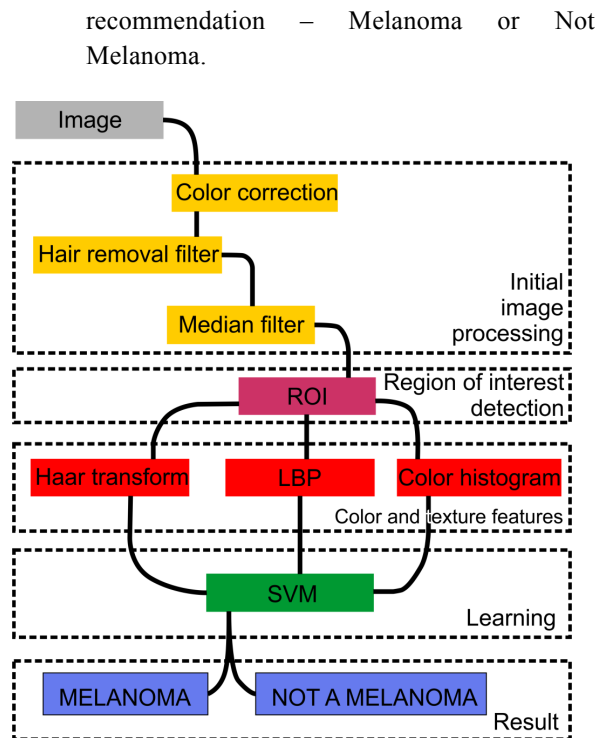


Fig. 4 Algorithm of automatic lesion detection.

Initial image processing consists of constant noise subtraction and histogram correction in order to increase image contrast and to use full available dynamic range. Fig. 5 demonstrates a histogram of the same image before and after this histogram processing. Histograms of values of all color channels together are shown here. Number of brightness levels is not equal due to the image color depth being converted from 48 (3 channels $\times$ 16 bits) to 24 (3 channels $\times$ 8 bits) bits on this step. Dynamic range of a resulting histogram may be controlled by a contrast setting while its horizontal shift may be controlled by a brightness setting. Described algorithm uses such properties that 1% of pixels occur to be beyond of the possible limits, this way dynamic range is fully used and “hot” pixel noise level is decreased.

Region of interest (ROI) detection. This step’s aim is to divide an image by an area related to lesion and another area that belong to healthy skin. K-means clustering algorithm [21] based on pixels’ brightness is applied to the image, that produces 40 (predefined feature) clusters to cover of possible values of brightness with minimal step. The whole brightness range is divided on sub-ranges according to the number of clusters, thus each sub-range represents one cluster. 10% of clusters with the least brightness are forcibly assigned to be related to a lesion, the rest of the clusters are assigned to represent surrounding healthy skin. Contrariwise, the image is spatially dividing by 2D blocks, and the amount of “lesion” pixels is calculated for each block. If there are more than 5% of such pixels, the block is marked as belonging to the ROI. The size of these blocks is determined in the following way: there are 20 blocks along the smallest image dimension, the

number of blocks along the largest dimension is calculated based on that the ROI blocks are squares.

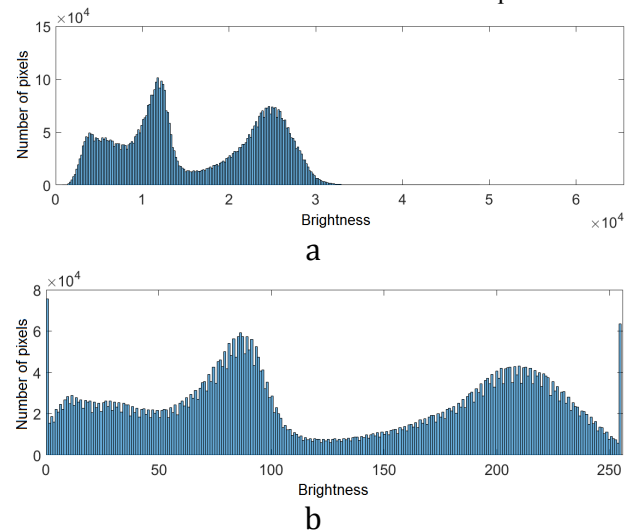


Fig. 5 Histograms of the initial image and of the image after processing. (a) Initial image histogram (3 channels, 16 bits); (b) processed image histogram (3 channels, 8 bits).

Color and texture features evaluation. Several approaches are being used on the features detection step. Result of each approach forms a part of the overall feature vector: Haar transform forms H_i vector, Local Binary Patterns approach forms L_i vector and color analysis defines C_i vector. These vectors are combined together in one vector later.

Haar transform

First, discrete three-layer Haar transform [22] is performed for each detected ROI block by using two filters: a high-pass and a low-pass filter. This is done here with the following algorithm:

- 1) These filters are applied to each row of the initial image resulting in two matrices: one contains approximated part and another contains fine details of the initial image.
- 2) This transform is then performed again for each column of these matrices, resulting in four total matrices, containing an approximated part and horizontal, vertical and diagonal details of the image.

Three layer Haar transform results 10 sub-images, as it is shown in Fig. 6 as an example. Haar transform is performed on a grayscale image created from the initial color one. A vector of mean value and dispersion of sub-images are calculated and combined in a feature vector for every ROI block. Thus, the number of feature vectors equals the number of ROI blocks for every image. ROI blocks are then clustered using k-means algorithm (10 clusters), and, finally, the histogram H_i for each image showing the distribution of the image feature vectors of clusters is calculated.

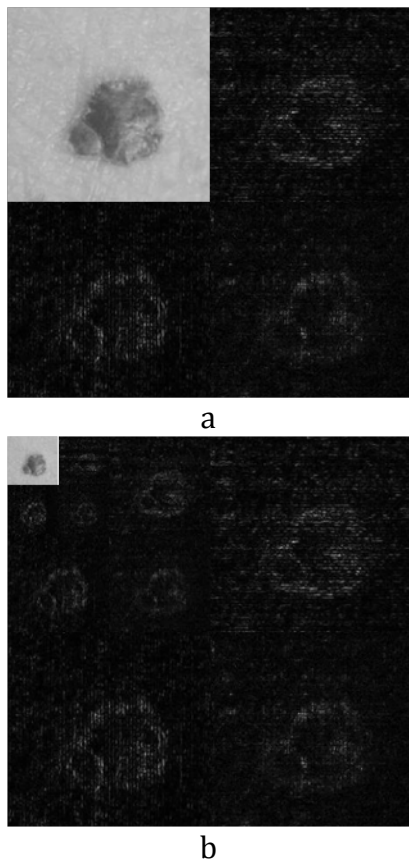


Fig. 6 Example of the Haar transform with different levels. (a) Result of the one layer Haar transform; (b) result of the three layer Haar transform.

Local Binary Patterns (LBP)

In addition to Haar transform, texture information is extracted using Local Binary Patterns (LBP). The main idea of LBP is to construct a p-bit number for every RGB image pixel by comparing its brightness with the brightness of p surrounding points using the following algorithm:

- 1) These points are located on a circle with the radius r , as it is shown in Fig. 7. Neighboring pixels' values are interpolated if the point is not exactly on any pixel;
- 2) brightness of the initial pixel is used as a threshold;
- 3) if a surrounding point value is more than the threshold, corresponding bit in the number is set to 1, and 0 otherwise.

The program uses two LBP algorithms with following parameters: $p = 16, r = 2$; $p = 24, r = 3$. The results are combined into a single 40-bit number. The resulting vector is normalized and this is what forms a vector L_i used for classification as a part of a general feature vector.

Color analysis

Color histograms are also used for the classification as a part of the features vector. Brightness range of every color channel is divided on P fixed intervals and

pixel brightness distribution is calculated for every channel in RGB, HSV and LAB color spaces in terms of these intervals. Different color spaces may be considered as different representations of the same data, which could improve classification results. The histograms' standard deviation and entropy values are also calculated and added to the histogram data to define a vector C_i .

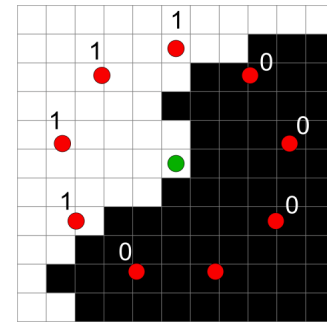


Fig. 7 LBP algorithm: an example of surrounding pixels selection and bilinear interpolation with central pixel as a threshold.

Comparative features

A comparative analysis method is used to improve classification of this classifier. All features are evaluated separately over the region of the lesion and over the region of the healthy skin (Fig. 8), and then the difference between these areas is calculated using Euclidean distance and cosine measure (Eq. (1) and Eq. (2)).

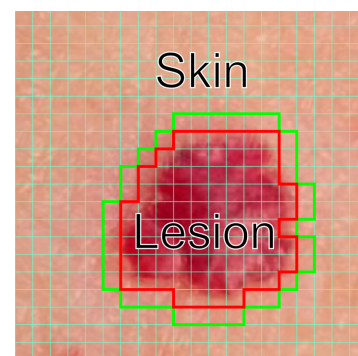


Fig. 8 Normal skin (green) and lesion (red) regions.

The Euclidean distance between the vectors $\bar{s}$ and $\bar{t}$, which are represented features vectors from Normal Skin and Tumor (Lesion) respectively (Fig. 8), is defined as

$$d_E(\bar{s}, \bar{t}) = \|\bar{s} - \bar{t}\|. \quad (1)$$

The cosine measure between the same vectors can be formalized as

$$d_{cos}(\bar{s}, \bar{t}) = \frac{\bar{s}^T \bar{t}}{\|\bar{s}\| \|\bar{t}\|}. \quad (2)$$

If this comparative mode is enabled, then, finally, exactly comparative features are considered. H_i , L_i and C_i vectors are replaced by corresponding comparative vectors without their size change.

Classification

Resulting features vectors from every method (H_i , L_i and C_i) are concatenated in a single vector for every image as shown in Fig. 9. Linear SVM method is used for classification [23].

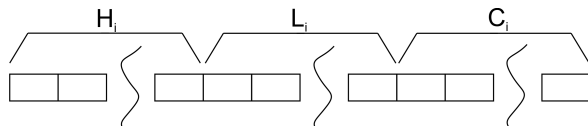


Fig. 9 Resulting vector concatenation.

Cross validation

Cross validation has been used to test the adequacy of the obtained classification model. One cross validation cycle includes dividing data into two parts, classifier training using one of the parts (training set) and validation using the other part (test set). Different cross-validation cycles are conducted with data divided differently and all results of all cycles are averaged to lower the final result deviation. We used this approach due to the low quantity of samples available. It allows us to estimate classifier's performance with various sizes of training and testing parts.

2.3 Skin tissue samples

Dermatoscopic images were gathered *in vivo* using the dermatoscopy tool in Samara Regional Clinical Oncological Dispensary. This survey was approved by ethical committee of Samara state medical university. Reference diagnostics results (Table 1) were obtained by histological analysis in each case (except Hemangioma, Keratoma, diagnoses of which have been concluded after visual inspection only). Histological analysis reviews lesion's microscopic features, such as: tissue type, stage, penetration of the lesion into the surrounding tissue. The extracted after surgical resection material was fixed in 10% neutral formalin. Serial sections were made (thickness up to 0.5mm), which were dyed with hematoxylin-eosin and picrofuchsin by Van Gieson method (Schiff reaction according to McManus).

3 Results

Two series of experiments have been performed in this study: classification of melanomas versus all other types, and classification of malignant lesions versus benign ones. The dataset was divided into two classes in each series: melanomas and non-melanomas (all remaining) in the first one; malignant (melanoma, basal-cell and squamous cell carcinoma) and benign (all remaining) in the second one. Classification of 36 melanomas and 37 non-melanomas dataset (Table 2)

result of 83.3% sensitivity and 70.3% specificity. In this case non-melanoma class consists of basal-cell carcinoma (18), nevus (12), keratopapilloma (7). With increased training dataset up to 205 samples, 169 of which are non-melanomas, classifier have predicted considerably worse result caused by properties of standard SVM algorithm settings. This is related to classes sizes being initially significantly unequal. In fact, a classifier is most efficient on classes having almost equal sizes. Therefore, presented results prove this condition.

Table 1 Tested skin samples.

Disease type	Number of tested samples
Fibroma	14
Keratopapilloma	12
Nevus	39
Melanocytic dysplasia	4
Keratoma	27
Benign pigmented lesion	1
Granulation	1
Inflammation	14
Hemangioma	12
Bowen's disease	1
Squamous cell carcinoma	2
Basal cell carcinoma	42
Melanoma	36

Classifying 80 malignant and 80 benign lesions classifier has got sensitivity of 63.3% and specificity of 61.3%. In this case, classes consisted of following: "malignant" class included melanomas (36), basal-cell (42) and squamous-cell (2) carcinomas; "benign" class included nevi (39), keratopapillomas (12), undetermined inflammations (14), hemangiomas (12), Bowen's disease (1), benign pigmented lesion (1), granulation (1).

Detailed results of the classification and cross-validation are presented in Tables 2-5.

Classifier remains its sensitivity above 70% and its specificity above 63% with mean values of 83% and 65% respectively during cross-validation for classification of melanomas versus non-melanomas, as it could be seen in Table 4. It signifies the classifier's potential operability with bigger data volumes, but class size equality remained condition. Cross-validation for "malignant" versus "benign" classification gives us

sensitivity of 60.9% and specificity of 59.7%. It should be noted that cross-validation results in case 90%/10% data splitting are not relevant because of too small test dataset (4 and 8 images in different cases) which depends a lot on the images themselves, so the results are mainly accidental in this case.

Table 2 Melanoma versus non-melanoma classification.

Number of melanomas	36
Number of non-melanomas	37
Sensitivity, %	83.3
Specificity, %	70.3
Tp	30
Fn	6
Fp	11
Tn	26

Tp - True positive, **Fn** - False negative, **Fp** - False positive, **Tn** - True negative

Table 3 Malignant versus benign classification results.

Number of malignant lesions	80
Number of benign lesions	80
Sensitivity, %	66.3
Specificity, %	61.3
Tp	53
Fn	27
Fp	31
Tn	49

Tp - True positive, **Fn** - False negative, **Fp** - False positive, **Tn** - True negative

4 Discussion

The classifier shows the best result with training on classes of similar sizes. The classifier has got sensitivity of 83.3% and specificity of 70.3% with melanoma versus non-melanoma classification and sensitivity of 66.3% and specificity of 61.3% with malignant versus benign tumors classification. These results could be improved by hybridization of the proposed algorithm with other optical non-invasive methods, and creation of a multimodal algorithm for optical data analysis.

Comparing the proposed system classification accuracy with other diagnostic methods efficiency, results of skin tumors classification by SVM of dermatoscopic images are comparable with accuracy of ultrasound diagnostics, thermal imaging diagnostics, hyperspectral imaging and ABCD diagnostics.

Delpueyo et al. [10] used multispectral imaging with LED backlight followed by feature detection and classification. The best achieved sensitivity for MM is 87.2% with specificity of 54.5%. Tomatis et al. [12] used multispectral imaging with CNN and achieved sensitivity of 80.4% and a specificity of 75.6% for

classification of melanoma vs non-melanoma. Pagnanelli et al. [7] report that dermatoscopy with ABCD analysis provides sensitivity up to 78.4% and specificity up to 79.6% in melanoma vs non-melanoma classification for trained non-experts.

Table 4 Melanoma versus non-melanoma cross-validation results.

Dataset		Sensitivity	Specificity	Tp	Fn	Fp	Tn
90/10	90% (32/33)	81.3%	63.6%	26	6	12	21
	10% (4/4)	65.6%	72.8%	21	11	9	24
80/20	80% (29/30)	86.2%	63.3%	25	4	11	19
	20% (7/7)	75.9%	70.0%	22	7	9	21
70/30	70% (25/26)	88.0%	69.2%	22	3	8	18
	30% (11/11)	88.0%	65.4%	22	3	9	17
60/40	60% (21/22)	95.3%	72.7%	20	1	6	16
	40% (15/15)	95.3%	63.6%	20	1	8	14
50/50	50% (18/19)	94.4%	68.4%	17	1	6	13
	50% (18/18)	72.2%	61.1%	13	5	7	11
100/0	(73/0)	83.3%	70.3%	30	6	11	26

Tp - True positive, **Fn** - False negative, **Fp** - False positive, **Tn** - True negative

Table 5 Malignant versus benign lesions cross-validation results.

Dataset		Sensitivity	Specificity	Tp	Fn	Fp	Tn
90/10	90% (72/72)	65.0%	65.0%	52	28	28	52
	10% (8/8)	58.8%	60.0%	47	33	32	48
80/20	80% (64/64)	65.0%	62.5%	52	28	30	50
	20% (16/16)	57.5%	60.0%	46	34	32	48
70/30	70% (56/56)	65.0%	61.3%	52	28	31	49
	30% (24/24)	55.0%	60.0%	44	36	32	48
60/40	60% (48/48)	67.5%	63.8%	54	26	29	51
	40% (32/32)	66.3%	57.5%	53	27	34	46
50/50	50% (40/40)	66.3%	66.3%	53	27	27	53
	50% (40/40)	65.0%	61.3%	52	28	31	49
100/0	(160/0)	66.3%	61.3%	53	27	31	49

Tp - True positive, **Fn** - False negative, **Fp** - False positive, **Tn** - True negative

However, classification accuracy of a presented method is usually less than accuracy of Raman spectroscopy, confocal microscopy, fluorescence diagnostics and OCT implementation. Jørgensen et al. [13] report an 81% success rate for classification of basal-cell carcinomas vs actinic keratosis using OCT data with machine learning approach. Confocal microscopy and classification using 6 criteria score results in 91.9% sensitivity and 69.3% specificity for finding melanoma, as reported by Pellacani et al. [14]. Zakharov et al. [16] implemented detection of melanoma using phase planes with Raman scattering data. This approach resulted in a sensitivity of 77.7%, and specificity of 87.8%. Kong et al. [11] also used Raman scattering in conjunction with autofluorescence, which was used to select points for Raman spectroscopy. This diagnostics approach based on a spectral classification model resulted in 100% sensitivity and 92% specificity.

Obtained results may be promising for primary diagnostics use, as the proposed system is pretty simple in comparison to Raman or OCT systems. Meanwhile, classification accuracy is considerably better than diagnostics accuracy of a general practitioner, estimated as 25%–60% [3].

5 Conclusion

We have implemented a dermatoscopic software system for *in vivo* automatic malignant lesion detection. This system utilizes SVM classifier coupled with the feature detection algorithm. First, the algorithm performs image

preprocessing followed with the Region of Interest detection. This is followed by Haar transform, LBP and color features extraction on a feature detection step. All extracted features are represented as a single vector, which is then used by an SVM classifier for training or a lesion classification.

We performed an experiment of lesion detection using data gathered by a custom designed multi-spectral dermatoscope, using only images taken with white polarized backlight.

The result shows the possibility of using proposed approach in clinics. Further enhancement in skin lesions classification with proposed system is possible by the proposed algorithm parameters tuning, usage of other channels data or better initial image processing. Neural network classification is also possible, including network pre-training on images from dermatoscopic databases and further final training using images made with proposed tool to lower variation of results [8]. There are also opportunities to hybridize the device with other optical modalities.

Disclosures

All authors declare no conflict of interests for this manuscript and have no a financial interest in the materials used in the manuscript.

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