"Algorithms for the selection of aggregation and selection coefficients in methods of classification of skin lesions"

Łukasz Wąs

Institute of Mechatronics and Information Systems
Lodz University of Technology

Presentation plan

1. Goals, assumptions
2. Issues of IT acquisition
3. Research methodology
4. PCA method
5. Classification methods
6. Non-melanocytic pigmented lesions
7. Transformations of the color scheme as a pattern in bloom
8. Image segmentation process
9. The LOCAL BINARY PATTERNS (LBP) method as a descriptor for the classification of specific features
10. Developed Dermatological Asymmetry (DASM) Symmetry Measurement Scale
    Measure of Skin Lesions
11. Convolutional neural networks - Blue-White Veil detection

Goals

The presentation uses the results of research (in the form of images) obtained from the Medical University of Lodz. The tests were carried out in the study using a database of two types of images: dermatoscopic images (taken with the use of a dermatoscope) and traditional images.

The collected material was evaluated by experts in the field of medical sciences (dermatologists). These images were placed in the DERMDB database (designed and created by the author of the paper) in order to enable data analysis.

Goals

The DERMDB database stores data in a standardized and standardized form and in high availability mode. In addition, data from the PH2 database were used to achieve the objective of the study. The database was designed and built due to the increasing incidence of melanoma in recent times and has been conducive to the development of computer diagnostic systems for the classification of dermoscopic images

Unfortunately, there is a lack of reference databases with the use of which the research material can be evaluated, because the data are evaluated in different sets of images by their authors with different interpretations and effectiveness, and there are no public databases available that could be used in the evaluation (classification) process.

Methodology

In the process of acquiring research material and the database design procedure, the following tasks were defined:

1. Creating a color heat map taking into account color combinations, pigmented lesions, aimed at highlighting certain features important from the point of view of experts, such as pathways in the lesion.

2. Modified pattern analysis. The standard, together with the color (Hue) and the standard, leads to a diagnosis. A pattern consists of a multiple-repeated structure of a base element. In the next step, we extract a certain number of features from the pattern.

3. For each of the regions containing specific features, we extract the variance of one channel from a given area (region). The features that represent colors consist of from the average and variance of one channel in the RGB and HSV color space.

Methods of selecting diagnostic variables

Methods of selecting diagnostic variables, i.e. features

The study showed that in the process of classification and separation of one of the features of a specifically Blue-White Veil within a defined lesion, this feature can be classified using a binary classifier. Meaningful results were obtained using the CNN convolutional neural network, which assessed the presence or absence of a blue-white veil within the eruption.

The above interchangeable networks were subjected to the training process and the CNN VGG19 networks were additionally used as a training network, which was tested on prepared images taken from the PH2 database dataset.

Methods of selecting diagnostic variables

Factor analysis methods can be used to classify this "importance" from the point of view of the formal acceptance of importance as variations of the main components of correlated disease features of skin lesions, which are distinguished as eigenvalue loads of the correlation matrix

A statistical method was used to classify the research material, the aim of which is to describe the relationships between observed, correlated variables using as few unobserved variables as possible, called factors, or factors that are mutually uncorrelated.

Methods of selecting diagnostic variables

The research consisted in the analysis of pathological images of skin lesions and the detection of melanocytic and non-mealnicite lesions and complications based on the acquired expert knowledge (dermatological scales and Total Dermatology Score TDS), as well as factor analysis. Due to the wide spectrum of studies describing melanoma (ACS – American Cancer Society and European Cancer Information System (ECIS) statistics), it was decided to support general practitioners (non-specialists in the field of dermatology) in facilitating the process of diagnosing melanocytic lesions.

There are 2 main problems in the described dermatological diagnostics:

the separation of the skin lesion, understood as the correct classification and the

the isolation of a lesion on the skin, understood as a visual examination (A priori).

Pigmented nevi

The term "pigmented naevi" is used to describe skin lesions that are caused by the proliferation (i.e. multiplication of cells) of melanocytes of ectodermal origin (derived from the cells of the crested process). Pigmented nevi take various forms, from benign freckles and birthmarks to melanoma. Determining the right procedure for a specific lesion is quite a challenge for both dermatologists and primary care physicians, because melanoma is not difficult to overlook.

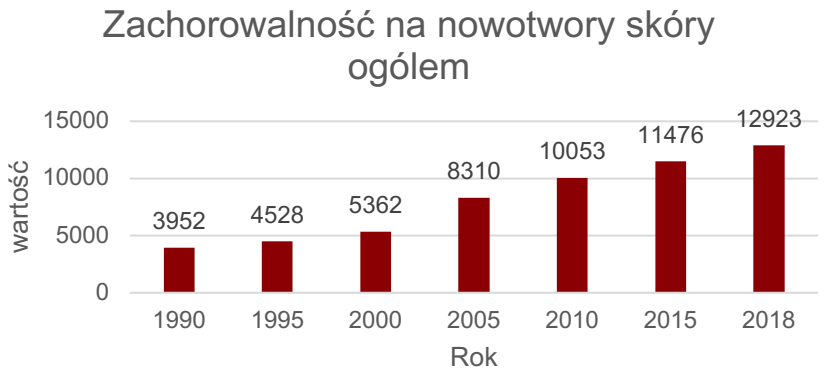


Fig. 1. Incidence of skin cancer in Poland in 1990-2018

Pigmented nevi

Rok 2018		Procentowy wskaźnik śmiertelności do zapadalności (Mortality to incidence ratio MIR)
1	Australia	11%
2	Niemcy	11%
3	Luksemburg	12%
4	Dania	12%
5	Szwajcaria	12%
38	Bośnia i Hercegowina	37%
39	Czarnogóra	38%
40	Rumunia	39%
41	Bułgaria	43%
42	Polska	46%

Rules and scales

In this case, medical recognition is the assessment of similarity to patterns, or the assessment of having properties specified for a class. The basis for the assessment are the quantitative characteristics of objects described from the domain side (dermatology) using rules and scales.

The use of a three- and seven-point scale in a specific clinical case of a specific patient is carried out using an interview conducted before the examination based on the knowledge of specialist doctors.

Structure

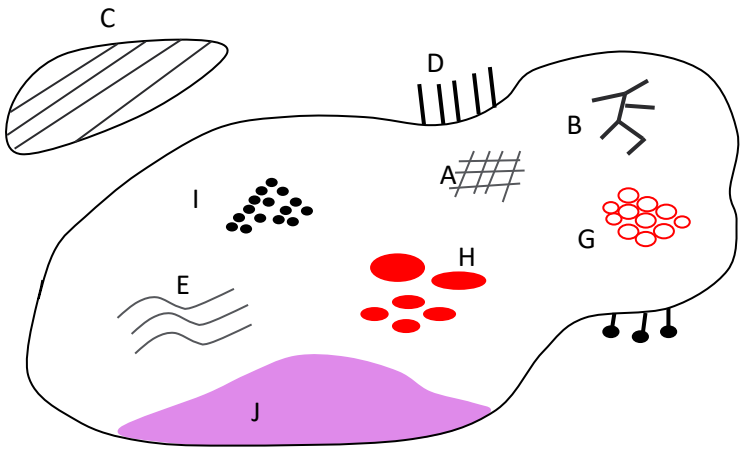


Fig. 2. Diagram of all the basic structures found in pattern analysis

Dyes

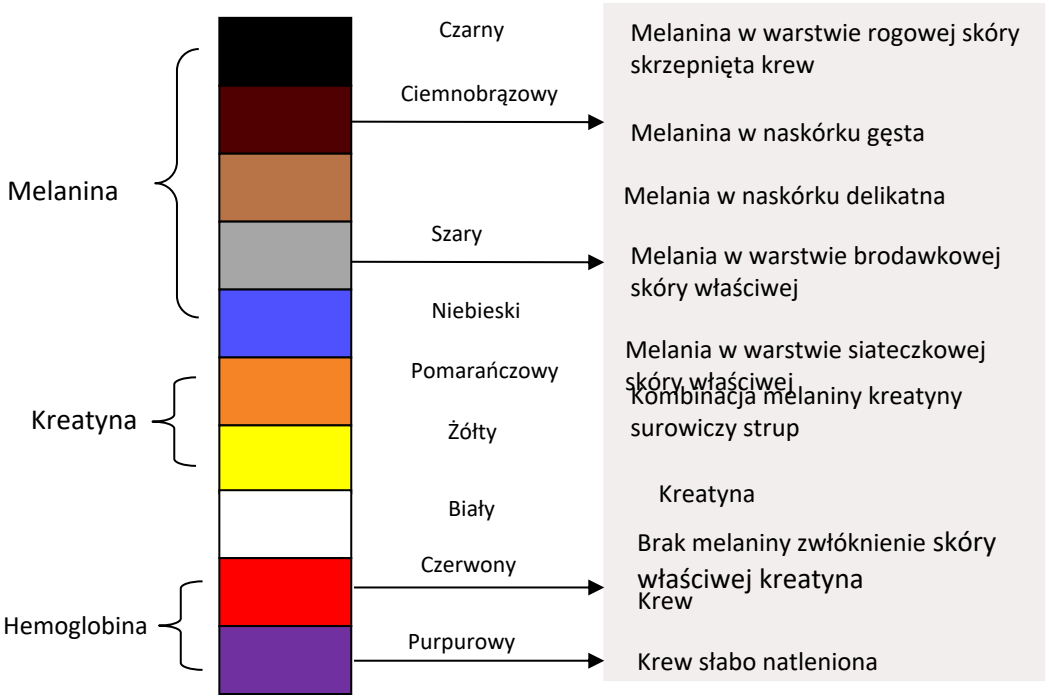


Fig. 3. Incidence of skin cancer in Poland in 1990-2018

Dermatological cases

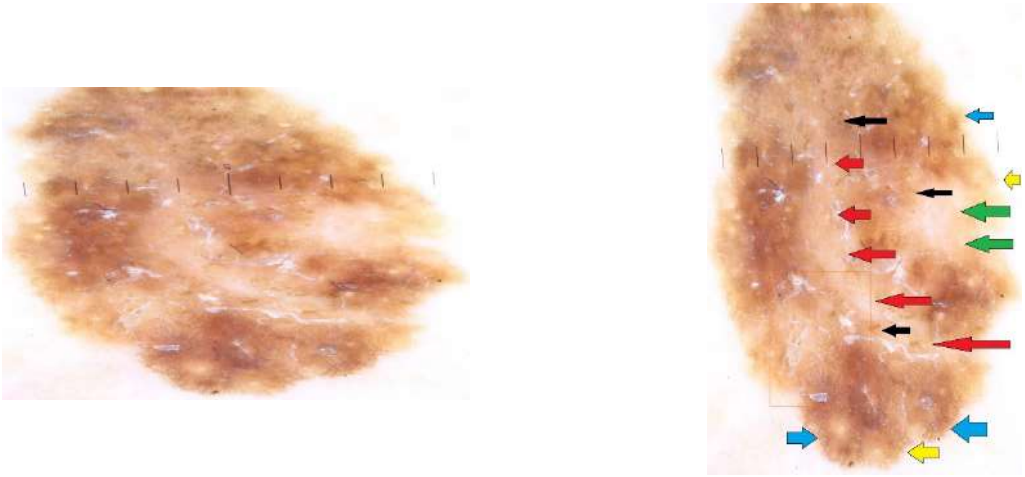


Fig. 4. - Description of the third practical case using scales in Figure a birthmark without indicating the elements in Figure b a birthmark in which the arrows determine the features

Panel

It presents research results on one of the standards defined by dermatologists using scales or rules, namely color/hue.

- Additional transformations of the "color scheme" are possible thanks to the use of a proprietary panel, in which it is possible to obtain a percentage of colors along with their graphical interpretation on the example of a histogram of the occurrence of colors from the RGB palette.
- The algorithm proposed in the paper for transferring information between color spaces operates within one pixel or its surroundings depending on the initial conditions set to the algorithm, replacing each of the components, starting from the R component to RGB, the G component to RGB and the B component to RGB.

Panel

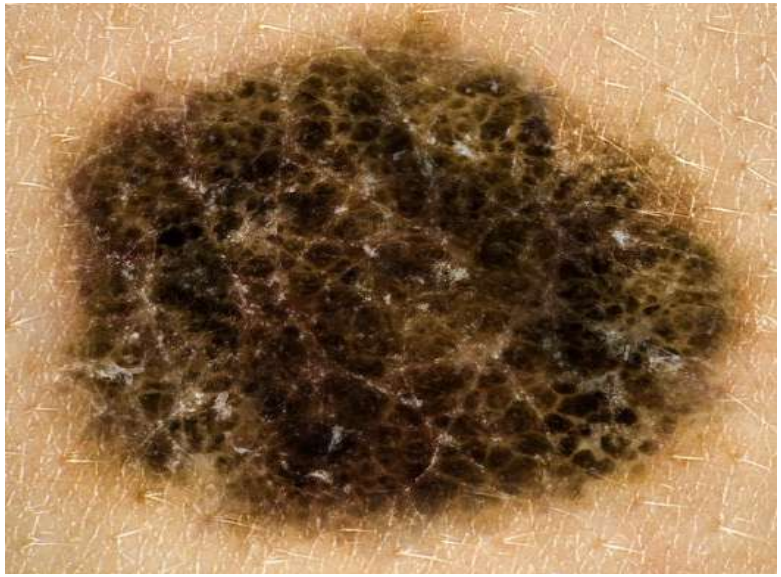


Fig. 5. Skin lesion

Fig. 5 shows the lesion grid with more visible edges and colors in order to properly reflect the actual shape (range) of the lesions. This allows you to isolate elements in the image

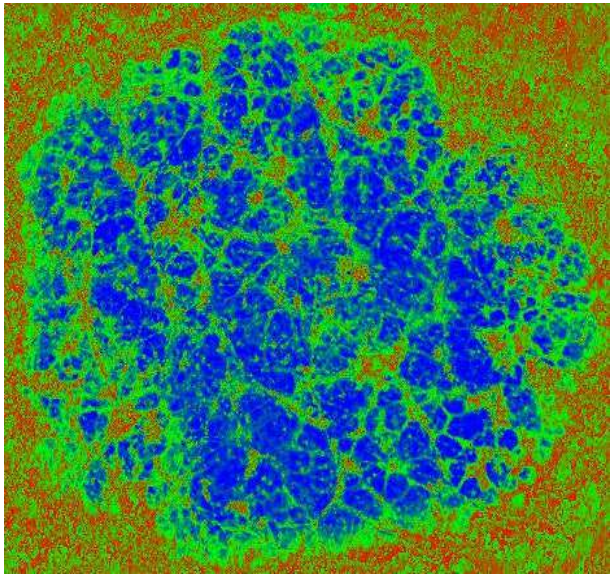


Fig. 6. Structural heat map

Next, (Fig. 6), a structural heat map is created, thanks to which it is possible to transfer information between color spaces and operate within one pixel or its surroundings. This allows you to make substitutions for each of the components, starting with the R to RGB component, the G component to RGB, and the B component to RGB.

Panel

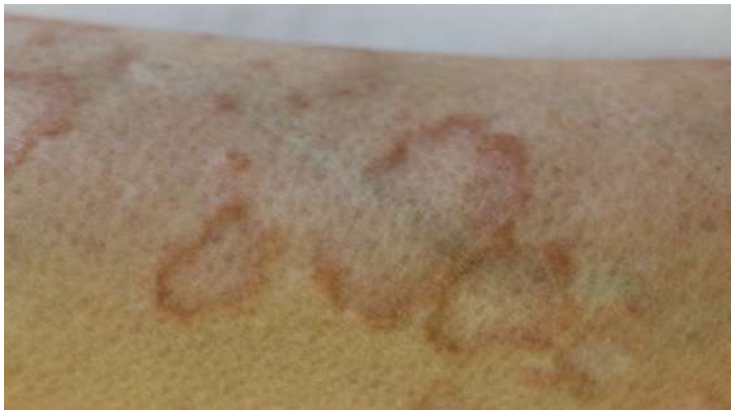


Fig. 7. Skin lesion

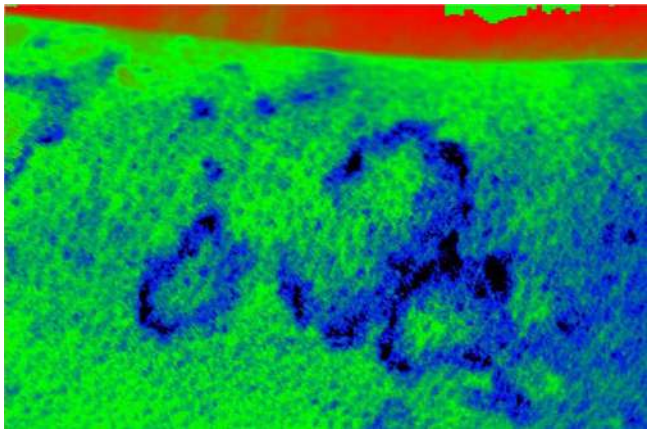


Fig. 8. Skin lesion in a modified color scale

Fig. 8 shows the efflorescence (Fig. 6.3) in a modified color scale that replaces each of the components, starting from the R to RGB component, the G component to RGB, and the B component to RGB. This process leads to the manipulation of one of the disease features, i.e. color. Thanks to color manipulation, it is possible to make diseased tissue more visible than healthy skin, which leads to easier identification of lesion areas. Subsequent operations on the skin lesion image are shown in Fig. 9 and Fig. 10.

Panel

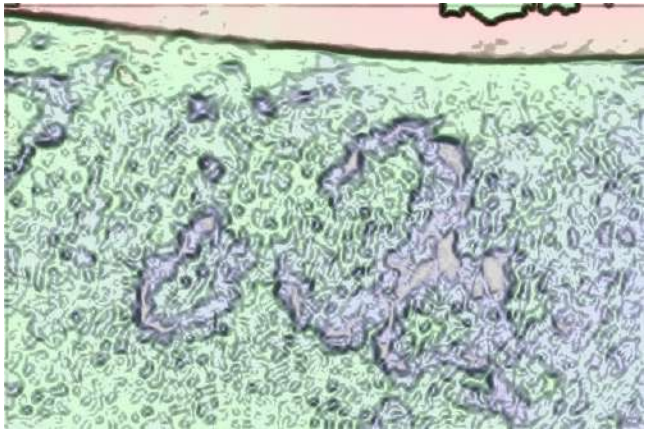


Fig. 9. Skin lesion with edges

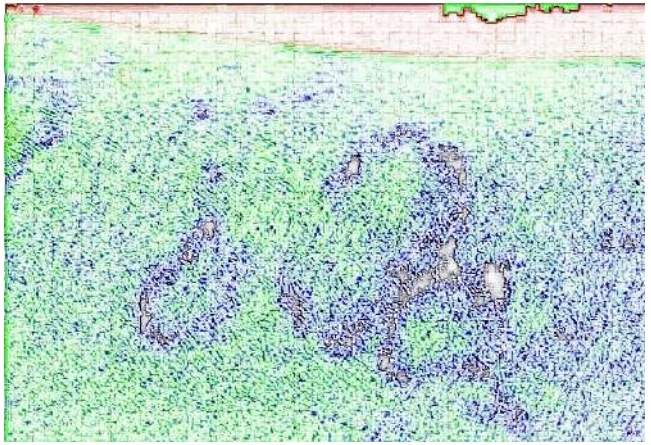


Fig. 10. Skin lesion granule map

For the case from Fig. 9, the algorithm of finding shapes according to the assumed patterns was used. It leads to the analysis of the pattern, which in turn accelerates the diagnosis process according to the progress of the process of searching for the pattern along with the color (hue). Fig. 10 shows a granularity map, which is also used for pattern analysis in order to effectively locate the lesion region where disease foci occur.

A heat map is a data visualization technique that shows the magnitude of a phenomenon in the form of color in two dimensions. Differences in color can be due to hue or intensity, giving the reader obvious visual cues about how the phenomenon is focused or changes in space.

Segmentation

For the process of segmentation of the skin lesion image, the author uses a square superimposed on the image (described on a circle) by means of an approximation process to increase the contours of the skin lesion under study. The result of this operation is shown in Figure 12.

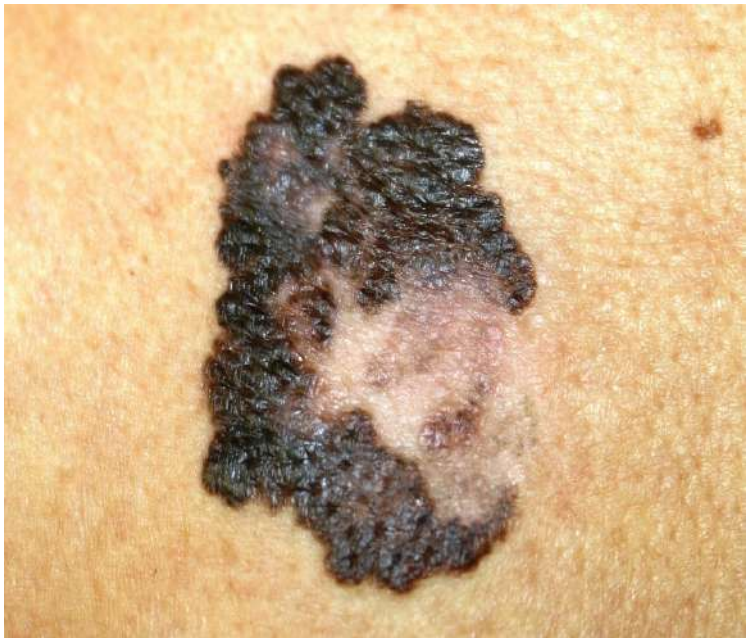


Fig. 11. Skin lesion

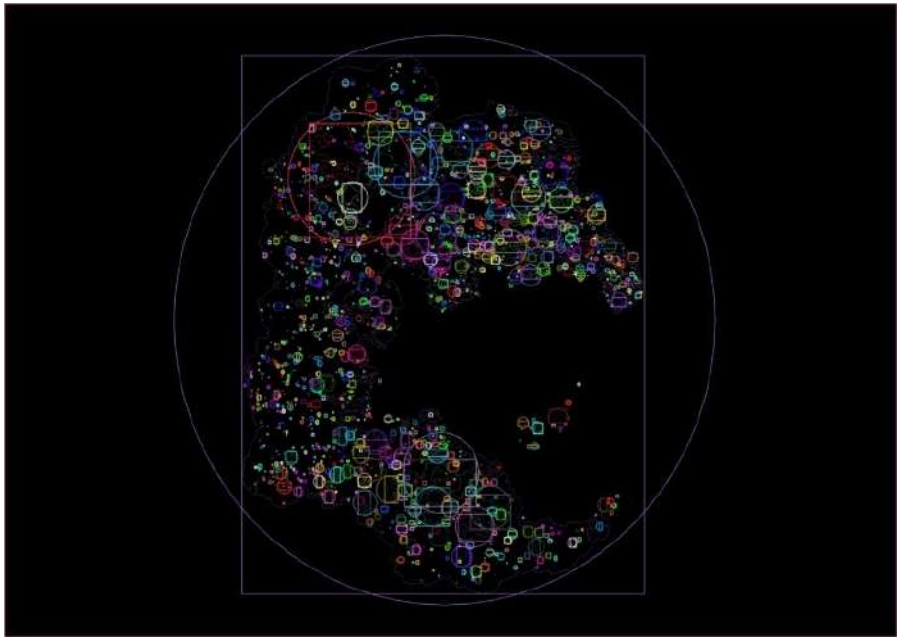


Fig. 12. Skin lesion with contours

Color manipulation

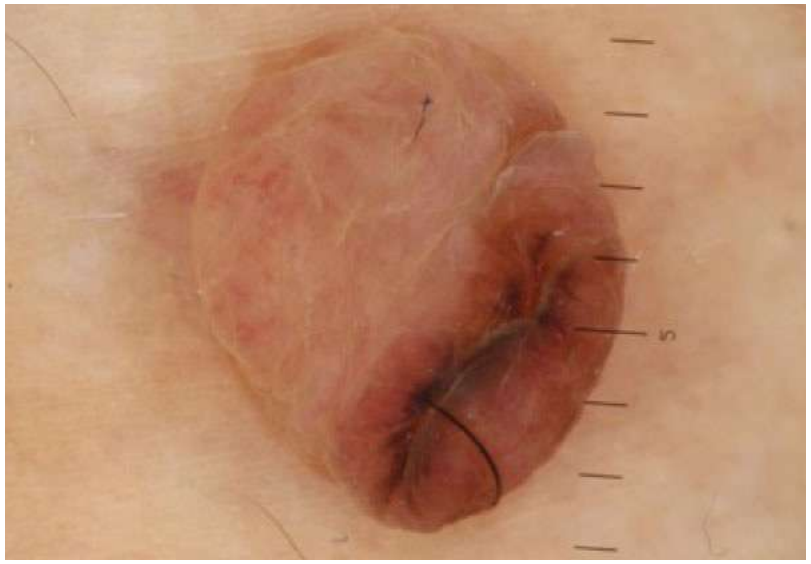


Fig. 13. Skin lesion

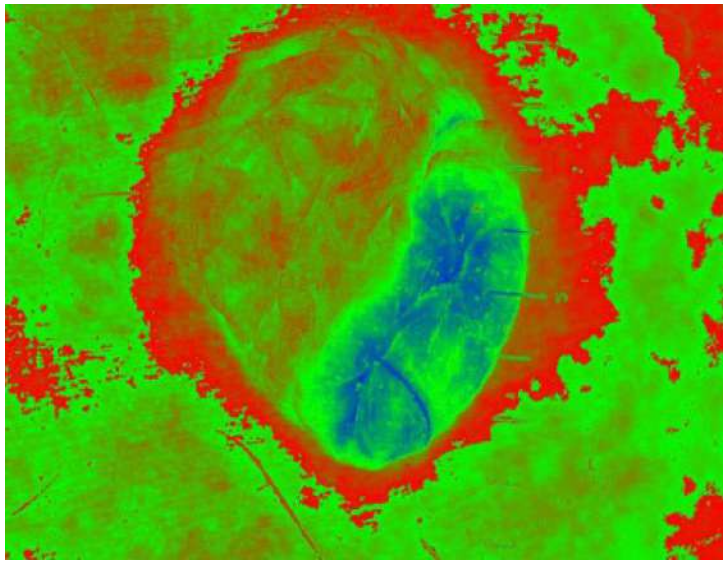


Fig. 14 Skin lesion

Figures 13 and 14 show the skin lesion given to the color manipulation process. The photos show the disease swap given to the manipulation of corals in the RGB color palette, which significantly shows healthy skin from the one that has the lesion.

Colour transformations

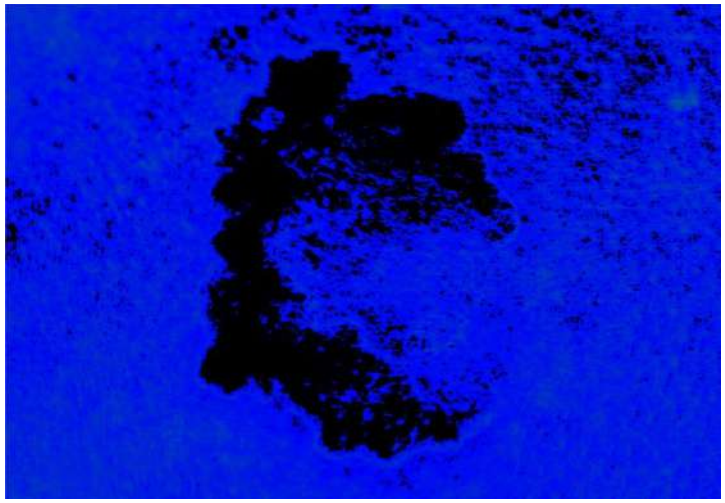


Fig. 15. Skin lesion with the use of colour transformation

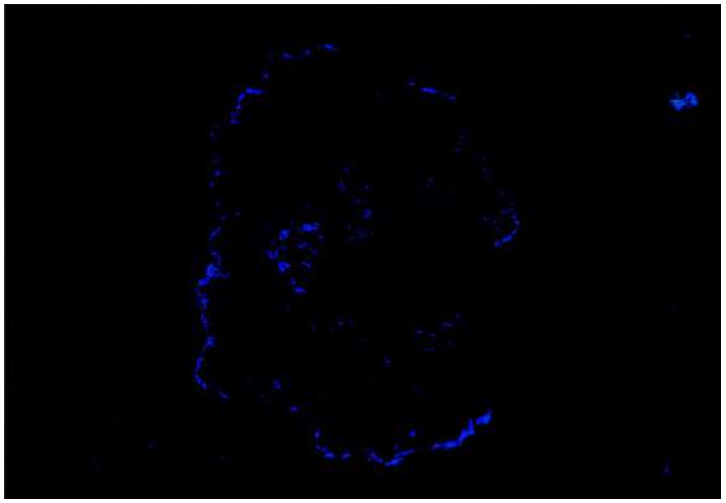


Fig. 16. Skin lesion with edge extraction

Fig. 15 shows efflorescence with the use of color transformation in order to isolate the region (range) of the lesion, which is then subjected to the process of extraction of the edge of the lesion in order to make it visible/exposed.

Colour transformations

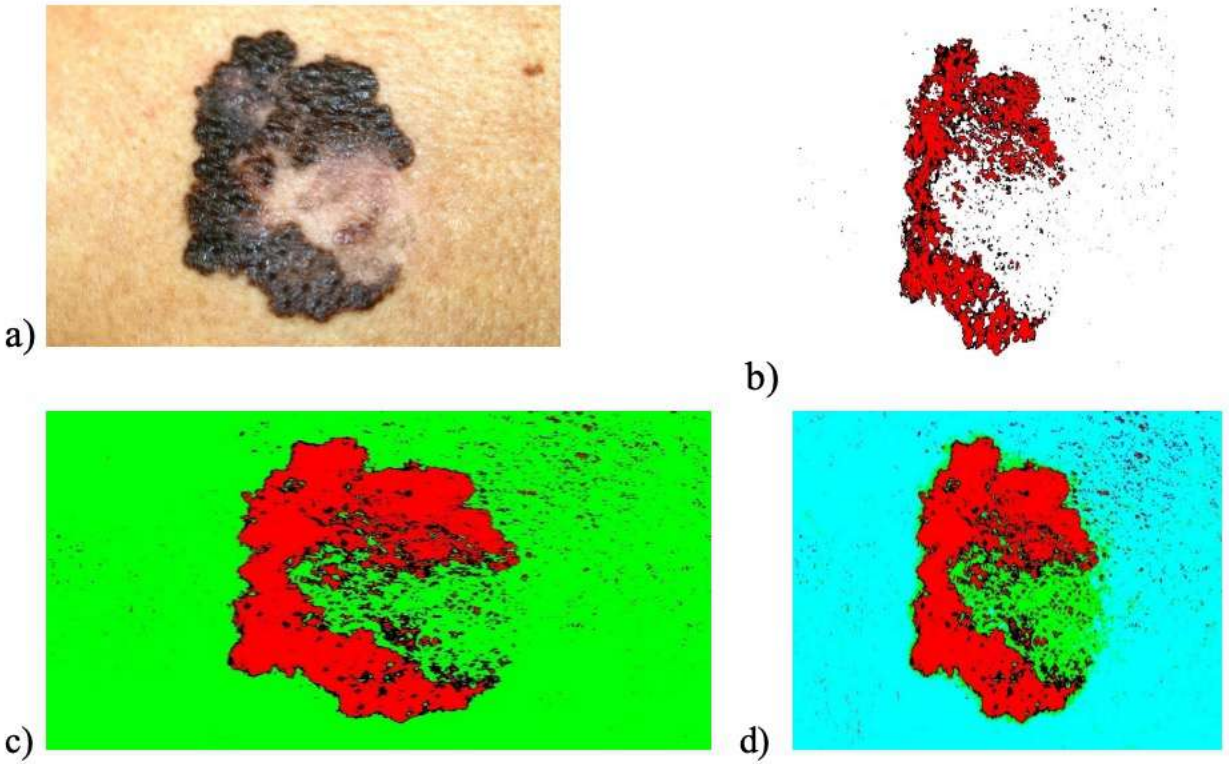


Fig. 17. Skin change after the colour transformation process

Filter for research material acquisition

In order to eliminate external factors that may have a negative impact on the collection of research material, such as images of skin lesions. These factors are mainly light intensity, lens angle, distance, and the organ on which the lesion is located.

The filter has been developed in order to eliminate the above-mentioned factors and, above all, to establish uniform conditions for the acquisition of research material. An extremely important aspect is the different angle at which the lesion can be located when taking a photo in order to eliminate errors. which may arise during the collection of the research material. In the corners of the filter, instead of rectangles containing color colors, we introduce a rectangular trapezoid, just like in AR (Augmented Reality).

Filter for research material acquisition

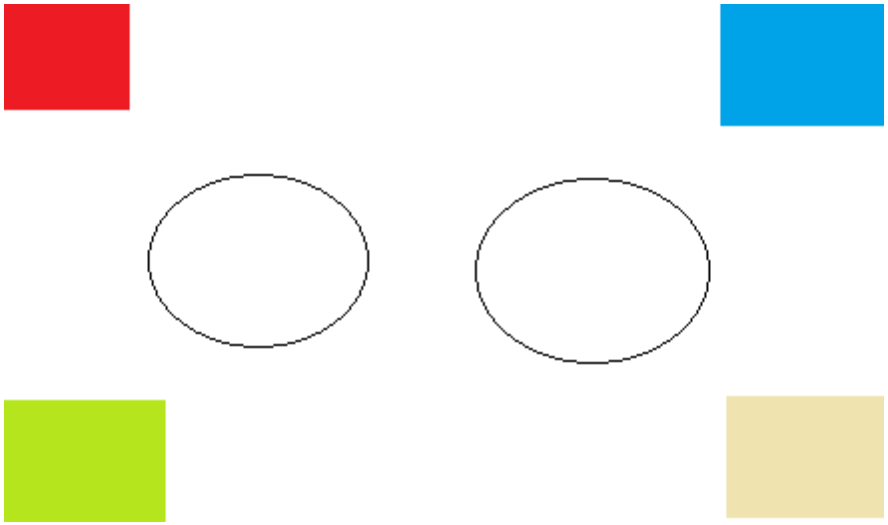


Fig. 17. Graphic illustration of the filter

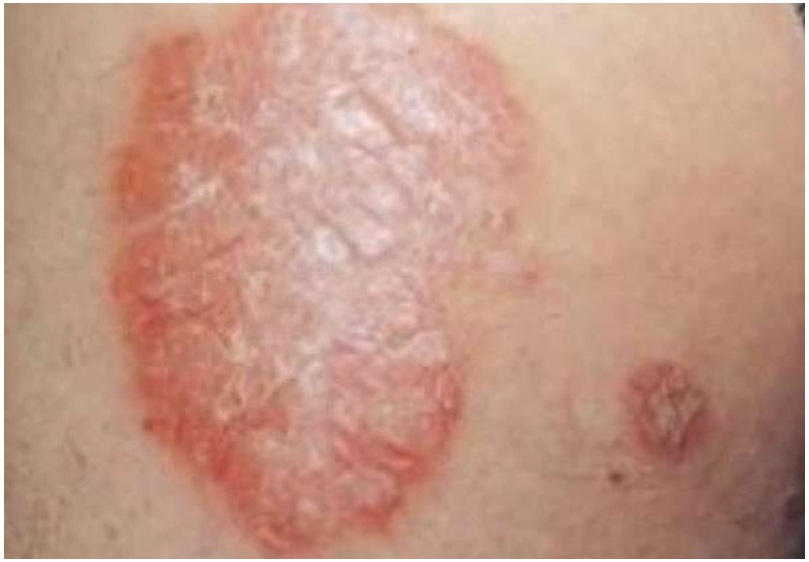


Fig. 18. Original photo of the skin swap

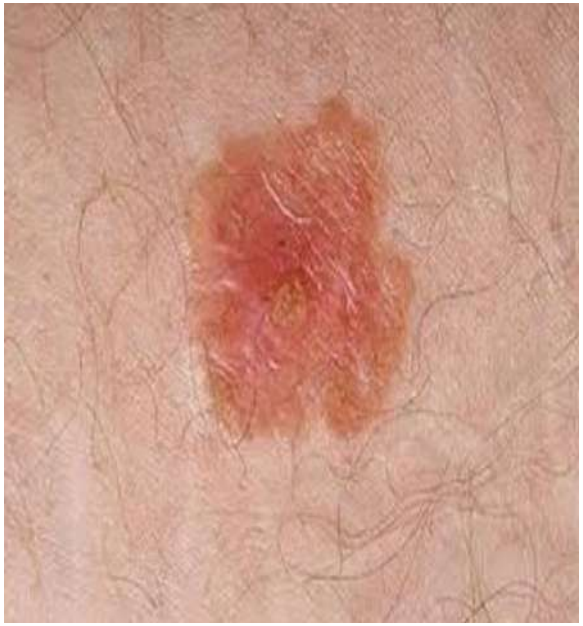


Fig. 19. Photo of skin lesion after segmentation

PCA Results

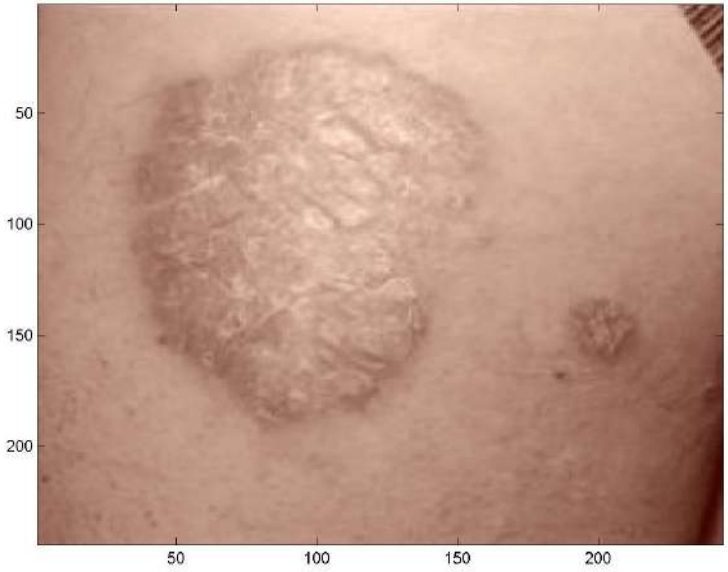


Fig. 20. Original photo of the skin swap

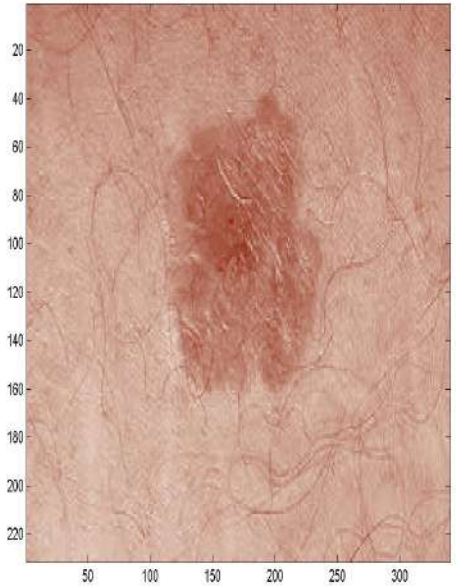


Fig. 21 Photo of skin lesion

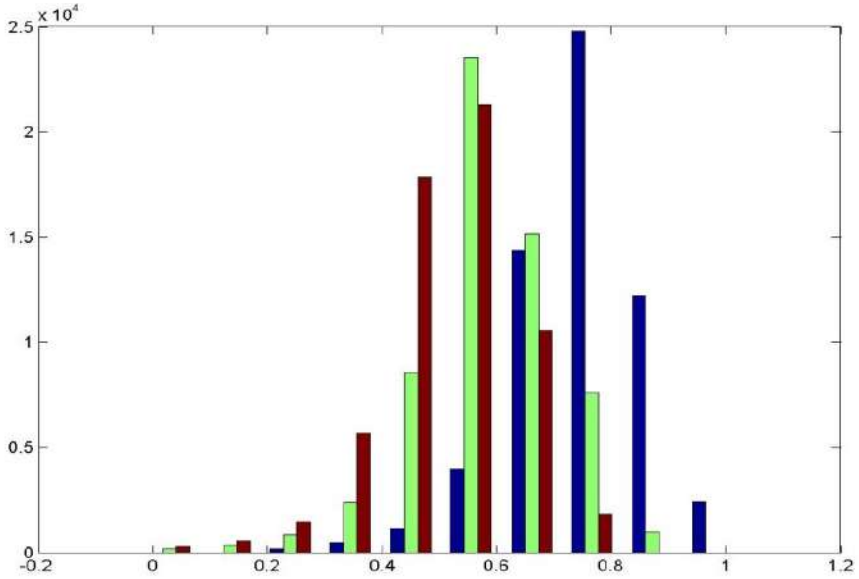


Fig. 22. Histogram of the image from Figure 20

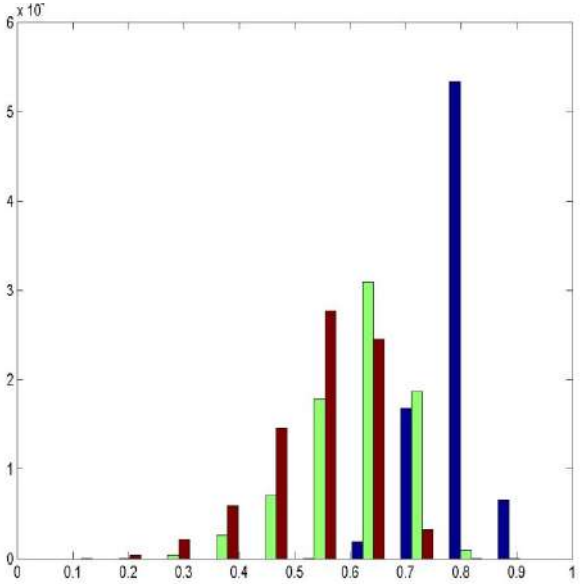


Fig. 23. Histogram of the image from Figure 21

The LOCAL BINARY PATTERNS (LBP) method as a descriptor for the classification of specific features

Skin lesions can be assessed using the total dermatology score (TDS) methodology, the 3-point dermatology checklist or 7-point rules, as well as the ABCD principle, among others.

The aim of further analysis is to verify the knowledge obtained from the PH2 database using the principles and rules described in dermatological textbooks.

The results obtained are confronted with the knowledge obtained from experts, using our own modified rules and proprietary scales (3PCLD and 7PCL), as well as using the neural network methodology.

LBP method(LOCAL BINARY PATTERNS)

The Local Binary Patterns (LBP) operator was originally designed to describe texture. The operator assigns a label to each pixel of the image; Thresholding the neighborhood of 3 x 3 of each pixel with the value of the middle pixel and considering the result as a binary number. The label histogram can then be used as a texture descriptor.

To be able to deal with textures at different scales, the LBP operator has been expanded to use neighborhoods of different sizes. Defining a local neighborhood as a set of sample points evenly spaced in a circle with a selected pixel allows you to obtain any radius and number of sample points. Bilinear interpolation is used when the sample point is not in the center of a pixel.

LBP method(LOCAL BINARY PATTERNS)

Fig. 24 Skin lesion from the PH2 base after the segmentation process

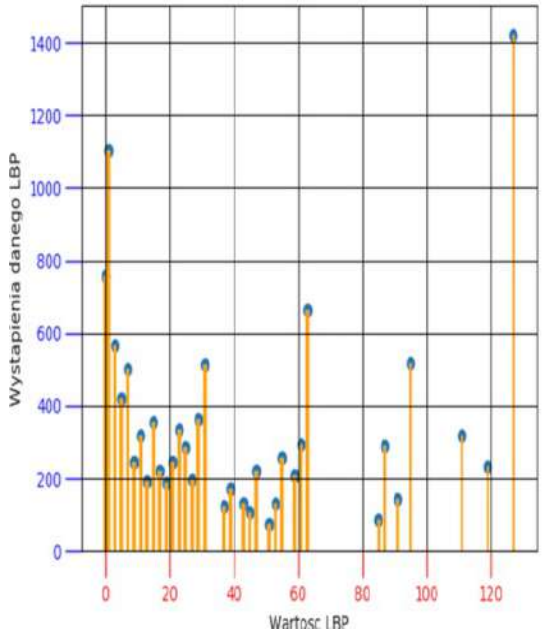


Fig.25. Occurrence of a given LBP from a specific image of the lesion

LBP method(LOCAL BINARY PATTERNS)

Fig. 24 Skin lesion from the PH2 base after the segmentation process

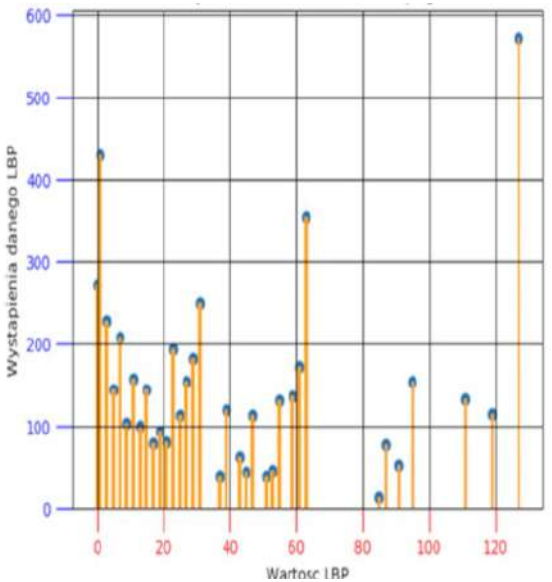


Fig. 25 Skin lesion from the PH2 base after the segmentation process

DASM (Dermatological Asymmetry Measure of Skin Lesions)

Developed Dermatological Asymmetry Measure of Skin Lesions (DASM)

Below are the results of research on the detection of one of the features defined by dermatologists using scales or rules in the form of asymmetry. The Dermatological Asymmetry Measure of Skin Lesions (DASM) coefficient for measuring the asymmetry of dermatological skin lesions developed by the author is presented below.

The numerical value of the coefficient was calculated numerically with the intention of introducing automation as part of the calculation of the number of axes of symmetry/asymmetry.

DASM (Dermatological Asymmetry Measure of Skin Lesions)

The Dermatological Asymmetry Measure of Skin Lesions (DASM) is presented below. The asymmetry of skin lesions depends on specific factors and is described depending on the shape, shade and structure.

In the above-mentioned databases, especially PH2, the values for calculating asymmetry are given as follows: encountered value 0 means fully symmetric, 1 means symmetrical in 1 axes, 2 means fully asymmetric. In order to achieve greater precision, specific values were adopted for the DASM.

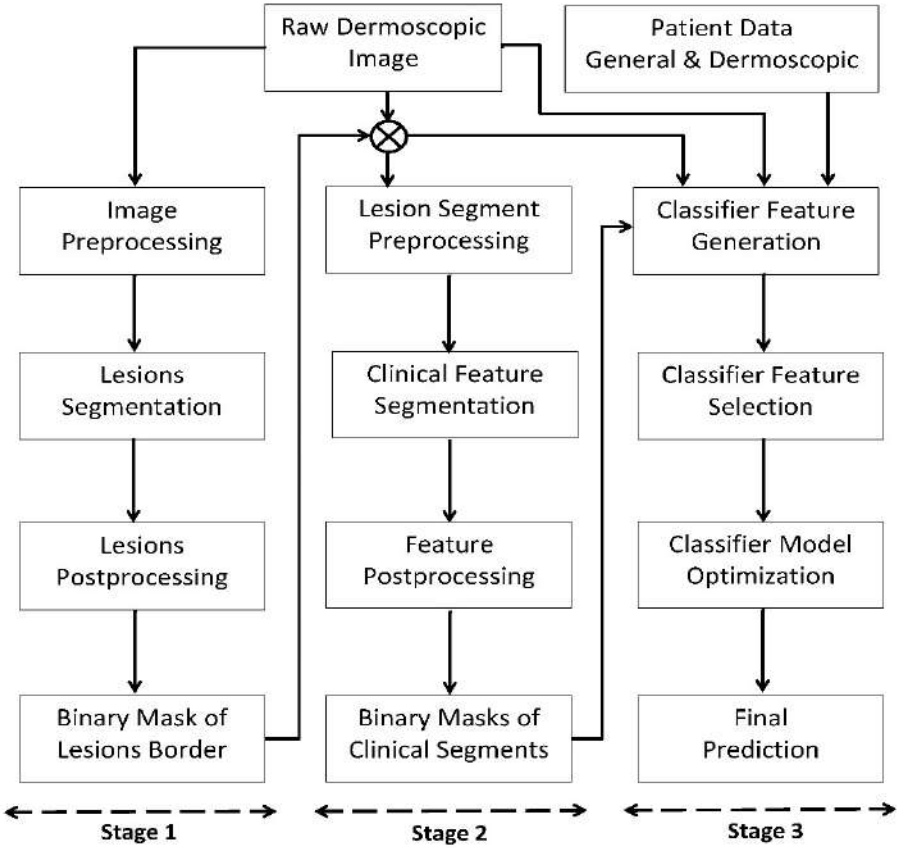
These values are continuous and are described as follows in specific intervals:

Shape <0, 2> (values 0,1,2)

Color/tint <0, 2> (values 0,1,2)

Structure <0, 2> (values 0,1,2)

DASM (Dermatological Asymmetry Measure of Skin Lesions)



- Fig. 26 General approach to the processing, segmentation and classification of skin lesions

DASM (Dermatological Asymmetry Measure of Skin Lesions)

After segmenting the lesion and the lesion features, we obtained binary masks, see Fig. 26.

The next step is to select the features to classify the lesion. We can use a 3-point checklist or a 7-point checklist. One of the features is the asymmetry of shape, shade and structure.

We prepared the DASMShape measure to estimate the asymmetry of the shape of the lesion. Shape, in our case the shape of change, means a binary mask of change.

DASM (Dermatological Asymmetry Measure of Skin Lesions)

In the first step, let's define:

DAS – Dermatological asymmetry, it is an asymmetry of shape, shade and structure. In dermatology, as we mentioned above, the asymmetry value can be: 0 for fully symmetrical shapes; 1 for symmetrical in one axis or 2 for asymmetrical.

DASM – Dermatological Asymmetry Measure – a measure of actual asymmetry depending on shape, shade/color and structure;

DASMShape – Dermatological Asymmetry Measure Symmetry/Asymmetry of Shape;

DASMHue – Dermatological Asymmetry A measure of symmetry of hue/color symmetry/distribution of asymmetry;

DASMStruct – Dermatological Asymmetry A measure of structure symmetry/asymmetry distribution;

DASM (Dermatological Asymmetry Measure of Skin Lesions)

- GSSPT - The geometric threshold of the symmetry of the binary shape of the change mask is the threshold that, after the axial transformation of the original binary mask and the mirror, are the same at least in the threshold value. PSSPT values are actual values from <0.1>, e.g. a threshold of 0.95 means that 95% of the mirror images coincide. The larger the threshold, the greater the similarity between the mirror images. The axis of symmetry, SAx, depends on the GSSPT as well as the number of axes of symmetry for a given shape.
- NSA – the number of axes of symmetry depending on GSSPT.
- VoSS – shape symmetry vector, it is a vector whose coefficients are equal to the number of axes of symmetry.

DASM (Dermatological Asymmetry Measure of Skin Lesions)

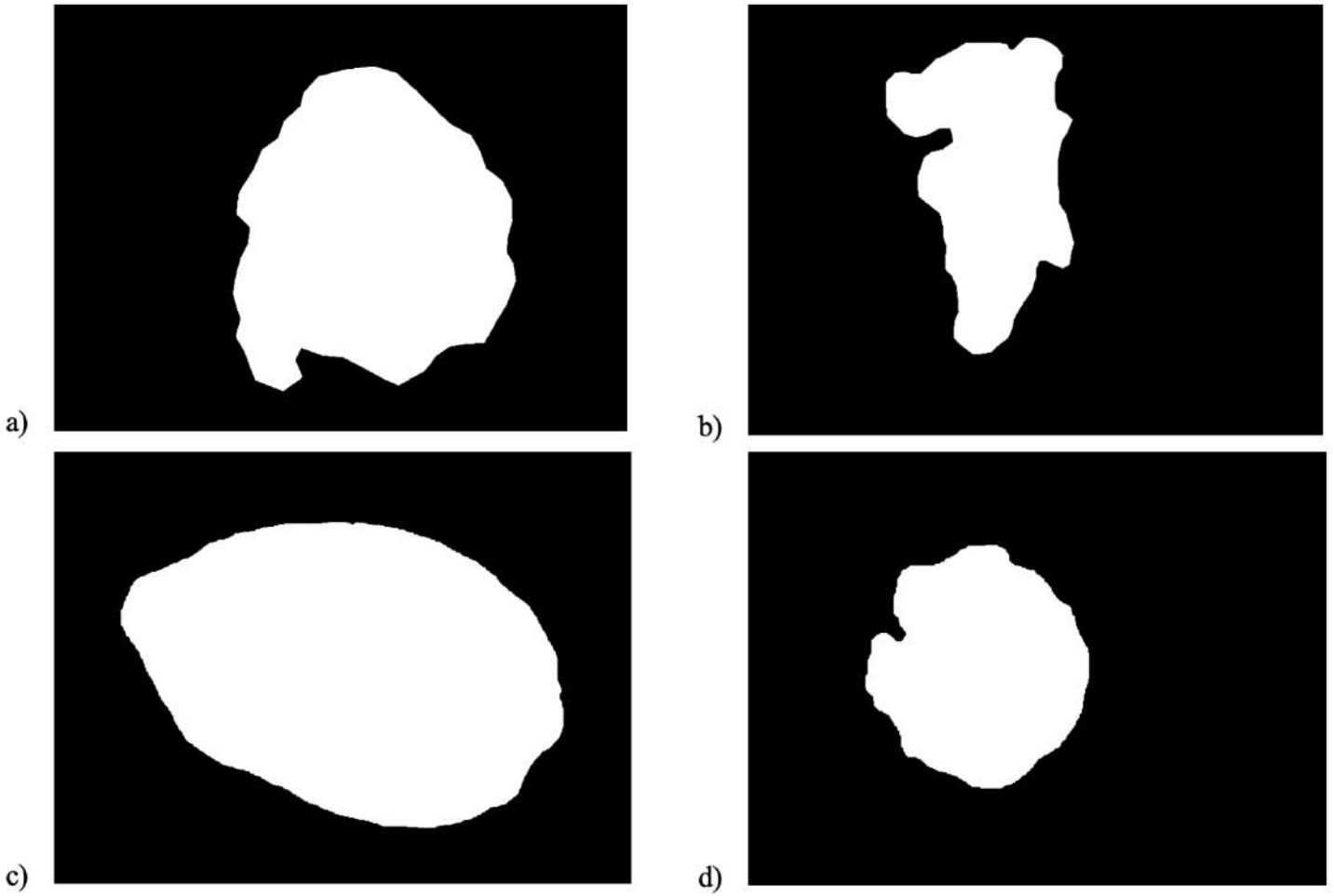


Fig. 2 The binary masks of the selected lesions from PH2 dataset [24] with dermatological asymmetry DAS.
a) IMD002 with DAS=1; b) IMD035 with DAS=2; c) IMD155 with DAS=0; d) IMD339 with DAS= 2

DASM (Dermatological Asymmetry Measure of Skin Lesions)

The method of deriving and estimating the new value of the measure of dermatological asymmetry can be described as follows:

Calculate the number of axes of symmetry for a given set of GSSPT n(ti) thresholds, where ti is the given threshold. After our experimental studies, we propose to select threshold values as a subset of the set:

{0.9, 0.91, 0.92, 0.93, 0.94, 0.95, 0.96, 0.97, 0.98}.

From the value of n(ti), construct the shape symmetry vector (VoSS) W:

$$W = [n(t1), n(t2),..., n(tk)] , (1)$$

where $k \geq 2$.

DASM (Dermatological Asymmetry Measure of Skin Lesions)

DASMShape, the Dermatological Asymmetry Measure of Shape, was designed as a VoSS function. Since DASM and DASMShape are real values with <0.2> we propose a positive, maximum-normalized to 2, and continuous measure as the exponent of the VoSS vector-dependent function:

$$DASMShape = 2 \exp (- f (W)) , (2)$$

where the functionf:$R^k \rightarrow$ R.

DASM (Dermatological Asymmetry Measure of Skin Lesions)

TABLE III. THE EXAMPLES OF **W** VECTOR FOR IMAGES FROM PH2 DATASET

Image ID from PH2	**VoSS vector W coefficient values**					***DASM Shape Exp***
	***n*(0.9)**	***n*(0.93)**	***n*(0.94)**	***n*(0.95)**	***n*(0.97)**	
IMD002	1	0	0	0	0	1.992016
IMD035	8	3	3	1	0	0.226233
IMD155	2	2	2	2	1	0.155229
IMD339	12	12	7	6	0	0.000000

DASM (Dermatological Asymmetry Measure of Skin Lesions)

Two types of features are proposed that have a positive, normalized to a maximum value of 2, and are continuous measures:

$$DASMShape(\mathbf{W}) = 2 \exp (- f (\mathbf{W}))$$

$$DASMShape(\mathbf{W}) = \frac{2}{f(w)}$$

DASM (Dermatological Asymmetry Measure of Skin Lesions)

Attribute		Cluster 0	1	2	3	4	5	6	7	8
Number of cases in the cluster		17	28	37	17	9	18	1	35	5
t1	mean	4.4722	1.417	2.0973	5.3928	11.0407	9.7959	16	2.1848	12.0002
t2	mean	3.0744	0.1588	1.4656	1.5592	7.3531	3.833	16	2.1032	11.6004
t3	mean	2.6403	0.0091	0.9879	0.6527	4.8398	2.3313	16	1.9997	9.0002
t4	mean	1.3528	0.0023	0.4964	0.3222	2.9785	0.7493	16	1.7029	7.2002
t5	mean	0.2846	0	0.0001	0.0023	0.49	0.0984	16	0.4121	1.6005
vector function	*f(W) Exp*	1.986907	0.008299	0.28387	0.24625	8.009417	1.628576	259.584	1.781331	33.98407
measure	DASExp	0.2742	1.9835	1.5057	1.5635	0.0007	0.3924	0.0000	0.3368	0.0000
asymmetry value		0	2	1	2	0	0	0	0	0
vector function	*f(W) Ratio*	3.78673	1.17734	2.04751	2.2101	6.95688	3.90879	33	3.46137	12.26071
measure	DAS Ratio	0.52816	1.698745	0.976796	0.904936	0.287485	0.511667	0.060606	0.577806	0.163123
asymmetry value		0	2	1	1	0	0	0	0	0

- Expectation–Maximization (EM) method with nine clusters.
- The parameters of EM method:
- max-candidates = 100,
- “minimum improvement in log likelihood” = 1E-5,
- “minimum improvement in cross-validated log likelihood” = 1E-6, and
- “minimum allowable standard deviation” = 1E-6 .

DASM

We used five machine learning methods to evaluate the clustering method. These methods provided us with the following validation results for 9 clusters:100% (3NN); 96.4% Multilayer Perceptron (MLP); 97.6% for binary tree C4.5; 100% Random Forrest (RF); 100% for SVM with Radial Base Function (RBF):

$$K(x,y) = \exp(-0.49*(x-y)^2)$$

The evaluation for classes defined by DASMShape methods showed that all evaluations were 100% or close to it.

DASM (Dermatological Asymmetry Measure of Skin Lesions)

In order to obtain a more accurate and automated process of recognizing lesions, which is the assessment of similarity to standards or the assessment of the possession of properties specified for a class based on quantitative characteristics of objects girded from the domain side (dermatology), the existing asymmetry was extended by adding asymmetry of shade and structure. The presented method provides for the division of asymmetry into asymmetry of shape, colour and structure.

Fig. 27. Skin lesion from the PH2 base after the segmentation process

Fig. 28. Skin lesion from the PH2 base after the segmentation process

Convolutional Neural NetworkVGG19

The study used the VGG19 convolutional neural network and images from the PH2 dataset

In the first step of the proposed algorithm, the images were reduced in size by cropping them to fit the pre-trained VGG19 network. From 768x568 pixel images, we obtained 224x224 pixel images; However, the proportions of lesions did not change.

As a result of the proposed methodology, we can be sure that the change is within the cropped square image. So we have the option of using the "Pooling Layers" layer so as not to miss the neighborhood of pixels.

Convolutional Neural NetworkVGG19

The problem with the PH2 dataset is that it contains only 200 images with 36 images containing a blue and white veil.

In order to expand the dataset and not lose the most important information about the classified features in the first step, I transform the images using isometric transformations, i.e. rotation by 90, 180, 270 degrees, mirror symmetry according to their horizontal and vertical axes.

In this way, the dataset was expanded to reach 1200 images, 216 of which contained a blue and white veil.

Convolutional Neural NetworkVGG19

As part of the process of identifying a given feature, a (blue and white veil) VGG19 network was used, which was additionally supported by the preparation of training and test sets, in which two approaches were presented, respectively BW1 and BW3.

- The BW1 set is divided as follows; 1000 images obtained by isometric transformations were used as a training set. The original photos were used as a test set, so we got 200 photos.

- The BW3 set is divided as follows. From the subset in which there is no blue-white veil, 27 random images and their isometric copies were taken from the collection; 162 images in total. We also added 6 random images and corresponding isometric copies to the test kit. We have 198 images in the test set. The remaining number of images was used as a training set. So I have 1002 paintings in the training set.

Convolutional Neural NetworkVGG19

- Strona 1

Tabela 8.1. Macierz błędów dla zbioru BW1 z dokładnością 94,5%

Wartość zbioru BW	Liczba zdjęć z określonego zbioru BW	A	P
A	164	158	6
P	36	5	31
Total	200		

Tabela 8.2. Macierz błędów dla zbioru BW3 z dokładnością 90,9%

Wartość zbioru BW	Liczba zdjęć z określonego zbioru BW	A	P
A	162	150	12
P	36	6	30
suma	200		

Tabela 8.3. Macierz błędów dla zbioru BW3, z dokładnością 90.9%

Wartość BW od PH2	Liczba zdjęć o podanym BW	A	P
A	162	150	12
P	36	6	30
suma	200		

Convolutional Neural NetworkVGG19

During the network training process, a model with 4 epochs and 400 iterations was used. For BW1, the average accuracy was 96.4±1.9%. For BW3, the average accuracy was 90.5±5.0%.

Selected factors derived from the error matrix are presented in Table 8.4.
As we can see, unlike accuracy, the true positive rate (TPR) is higher in the BW3 approach. This indicates the high sensitivity of the selected classification method.

Convolutional Neural NetworkVGG19

The false positive rate (FPR) for BW1 is lower than for BW3, but the value of 10.9±5.5[%] is satisfactory. The calculated F1 score and Matthews correlation coefficient (MCC) also show values closer to 1.

Therefore, the pre-trained VGG19 convolutional neural network shows very good results that can be used in dermatological evaluation using a three- or seven-point scale.

The false positive rate (FPR) for BW1 is lower than for BW3, but the value of 10.9±5.5[%] is satisfactory. The calculated F1 score and Matthews correlation coefficient (MCC) also show values closer to 1.

Convolutional Neural NetworkVGG19

Tabela 8.3. Macierz błędów dla zbioru BW1 I BW3

CM factor		BW1	BW3
ACC[%]	AVG	96.4	90.5
	VAR	1.9	5.0
	Min	94.5	82.8
	Max	99.0	97.0
TPR[%]	AVG	92.8	96.7
	VAR	2.8	10.9
	Min	83.3	83.3
	Max	100	100
FPR[%]	AVG	2.8	10.9
	VAR	2.1	5.8
	Min	0.6	3.7
	Max	6.1	21.0
F1	AVG	0.90	0.79
	VAR	0.05	0.09
	Min	0.85	0.68
	Max	0.97	0.92
MCC	AVG	0.88	0.76
	VAR	0.06	0.10
	Min	0.82	0.64
	Max	0.97	0.91

Convolutional Neural NetworkVGG19

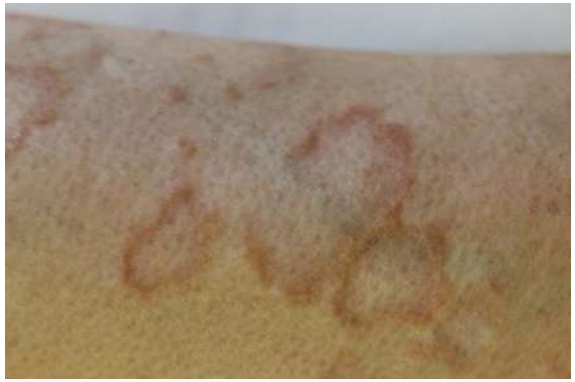
The false positive rate (FPR) for BW1 is lower than for BW3, but the value of 10.9±5.5[%] is satisfactory. The calculated F1 score and Matthews correlation coefficient (MCC) also show values closer to 1.

Therefore, the pre-trained VGG19 convolutional neural network shows very good results that can be used in dermatological evaluation using a three- or seven-point scale.

In my research, I used the CNN VGG19 network [10] and the PH2 dermoscopic image dataset [11]. The results achieved are quite promising. The average accuracy was over 90%. Networks usually classified the images of change quite well.

Paintings with a blue and white veil present were rarely unclassified. In five iterations, the Type II error was about 7.2% for BW1 and 3.3% for BW3.

Results



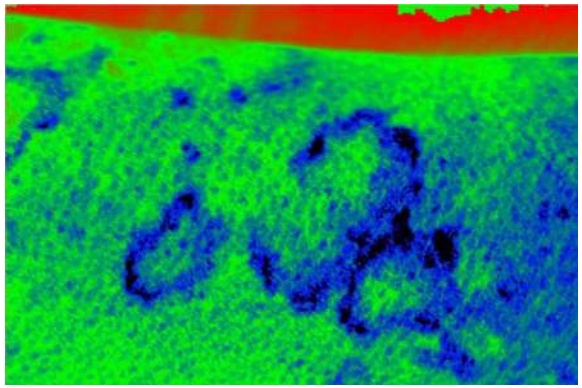


Fig. 29. Skin lesions lichen erythematosus with bara selection to isolate the lesion from the dermis

Results

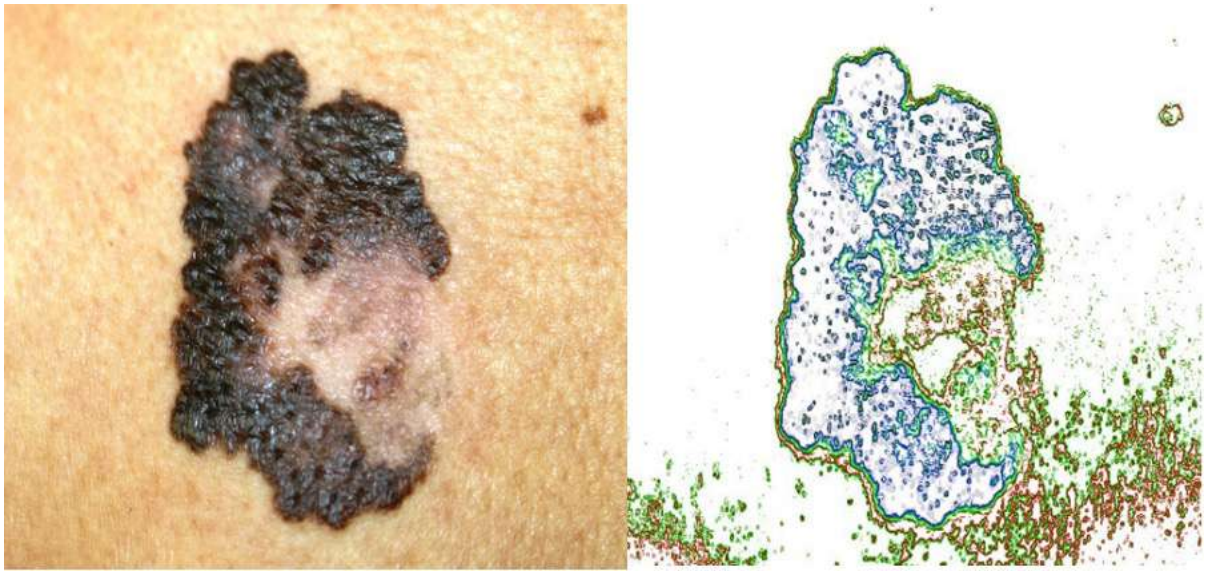


Fig. 30. Photos of the lesion
with granularity map

Results

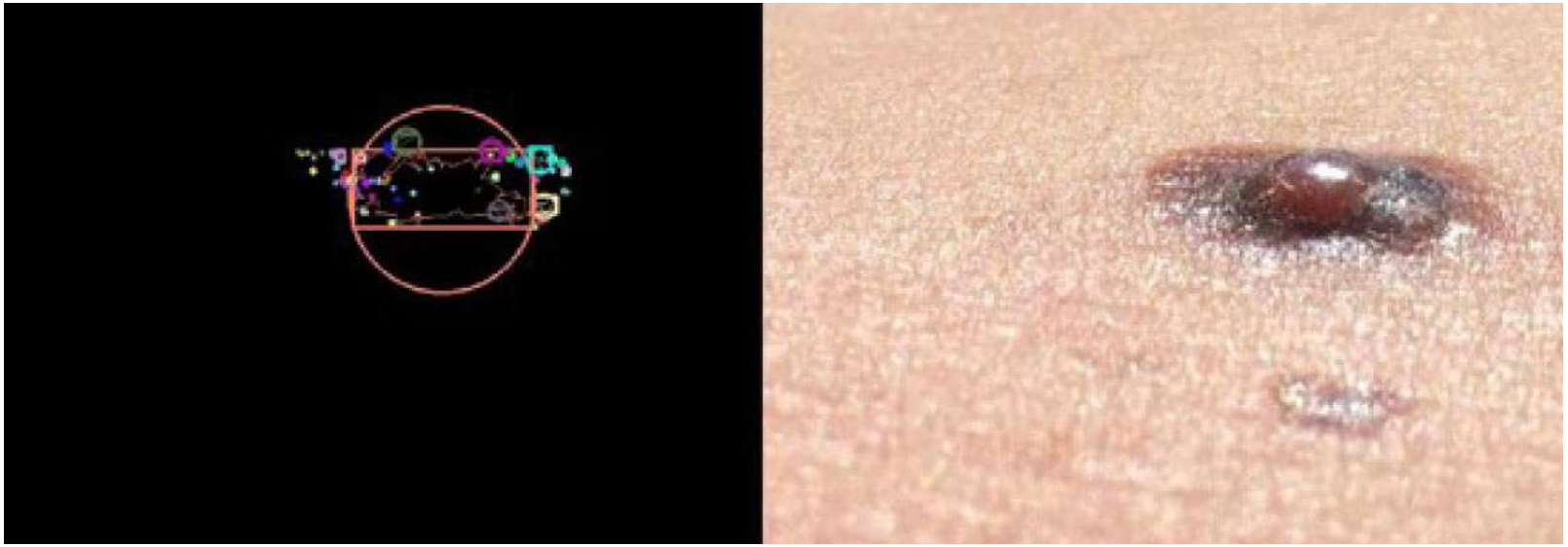
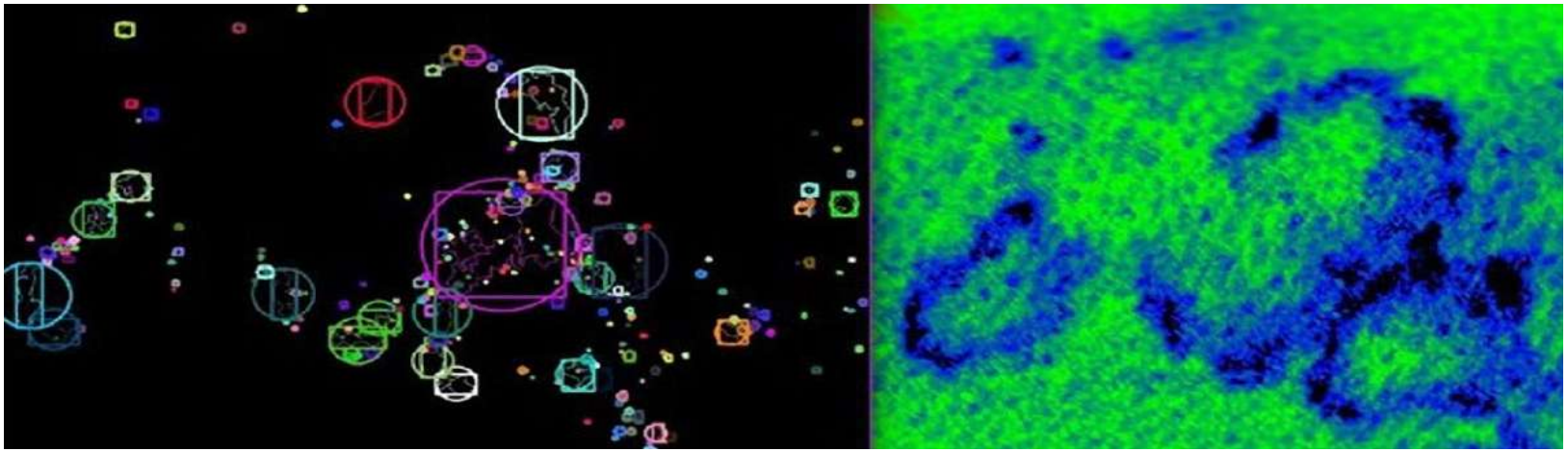


Fig 31. Lesion after pattern extraction surgery
which is a protuberance, i.e. a tumor

Results



- Fig. 32 Lesion after pattern segmentation surgery with defined contours

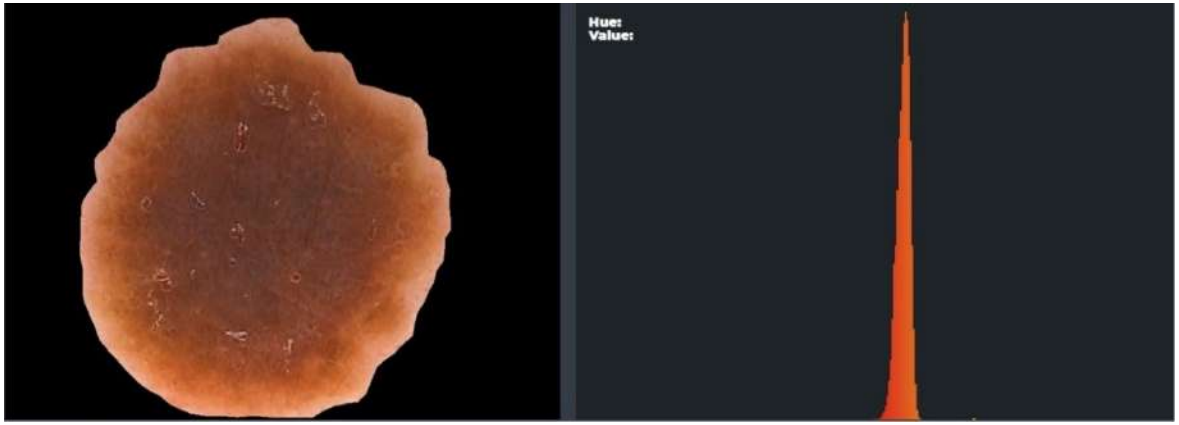
Results

With the help of the panel, it is also possible to determine the percentage of colors along with a graphical interpretation on the example of the histogram of the occurrence of colors from the RGB palette. In addition, it is possible to detect the percentage of specific features from the three-point dermatological scale on the basis of transformations and the occurrence of colors/colors characteristic of the three-point dermatological scale.

Results

Factor Occurrence	Percentage occurrence
Regression regions	0.046%
Blue and whitish veil	0.1193%
White color	0.2177%
Red color	0.2546%
light brown color	43.49%
dark brown color	52.11%
blue-gray colcor	0.7038%
Black color	2.96%

Results



Factor Occurrence	Percentage occurrence
Regression regions	0%
Blue and whitish veil	0%
White color	0.09%
Red color	0%
light brown color	28.03%
dark brown color	71.81%
blue-gray colcor	0.045%
Black color	0%

Thank you for your attention