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Skin lesion classification using relative color features

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Abstract

Background/purpose—Clinically, it is difficult to differentiate the early stage of malignant melanoma and certain benign skin lesions due to similarity in appearance. Our research uses image analysis of clinical skin images and relative color-based pattern recognition techniques to enhance the images and improve differentiation of these lesions.

Methods—First, the relative color images were created from digitized photographic images. Then, they were segmented into objects and morphologically filtered. Next, the relative color features were extracted from the objects to form two different feature spaces; a lesion feature space and an object feature space. The two feature spaces serve as two data models to be analyzed to determine the best features. Finally, we used a statistical analysis model of relative color features, which better classifies the various types of skin lesions.

Results/conclusions—The best features found for differentiation of melanoma and benign skin lesions from this study are area, mean in the red and blue bands, standard deviation in the red and green bands, skewness in the green band, and entropy in the red band. With the relative color feature algorithm developed, the best results were obtained with a multi-layer perceptron neural network model. This showed an overall classification success of 79%, with 70% of the benign lesions successfully classified, and 86% of malignant melanoma successfully classified.

Keywords

skin lesion; melanoma; relative color features; image classification; pattern recognition; CVIPtools

MALIGNANT MELANOMA, with 59,940 new cases and 7110 deaths in the US estimated in 2007 (1), is easily cured if detected at an early stage. To the total of 59,940 new cases of melanoma, we can add an estimated 48,290 cases of melanoma *in situ*, a number growing at 15% per year in some countries (2). Unfortunately, the accuracy of physicians in diagnosing melanoma in the clinic is not high. In a recent study, general practitioners had a sensitivity and specificity for detection of melanoma of 62% and 63%, while dermatologists had a corresponding sensitivity and specificity of 80% and 60% (3). Dermoscopy examination can improve melanoma diagnostic accuracy (4). Although digital analysis of dermoscopic images gives more accurate results than digital analysis of clinical images (5), there may be a role for analysis of clinical lesions, as combining clinical and dermoscopic examinations has improved melanoma diagnostic accuracy (4). In this project, automatic classification of

clinical images using relative color features was studied. Two types of benign lesion images Clark or dysplastic nevi and nevocellular nevi were used along with images of invasive and *in situ* malignant melanoma.

This paper illustrates the use of computer imaging and pattern recognition in the detection of skin lesions. CVIPtools (6), a computer vision and image processing software, was used to extract the relative color features from the segmented skin lesion images. In order to maximize the possibility of achieving the goal, two feature spaces, lesion feature space and object feature space, were established with different combinations of the features. The feature spaces serve as two distinct data models to be analyzed with Partek (7), a statistical analysis software package, for analyzing and determining the best features through experiments. The statistical analysis model based on the best features was then found to better classify the various skin lesions with a successful classification rate of 86% for detecting malignant melanoma. This is comparable with the clinical accuracy of dermatologists.

Materials and Methods

Image database

The original skin lesion images for this project were obtained from 35 mm color photographic slides. Digitization was performed on these images and the resulting digital images had a spatial resolution of 512×512 pixels, and a grayscale resolution of eight bits per color band, giving 256 possible intensity levels per color band. Thus, the color images obtained had a resolution of 24 bits per pixel, with each pixel having one of 16,777,216 possible colors. Border images are binary images, which represent the borders of the lesions (8). The borders were drawn manually and reviewed by a dermatologist for accuracy. These images were used to create 'Relative Color Images.' Both the lesion image and the border image were in PPM format and of the same size. The data type of the images was BYTE and the format was REAL. The data range was from 0 to 255. Relative color images were created to normalize the skin color and the lesion color. These images were created using a series of steps with the border images and original lesion images. The database used for this project contains 160 melanomas, 42 dysplastic nevi, and 83 non-dysplastic nevi images, along with their border images.

Software

Relative color images were used due to the variation of normal skin color, in order to develop robust classification algorithms. To analyze and classify the skin lesion, features were extracted from the relative color images using CVIPtools (6). CVIPtools is an image processing toolkit with more than 200 processing functions, and was used to process the images and extract the object features. To automate the process for all the images a Tcl script was created, which is compatible with CVIPwish and CVIPtcl (9), which are the shell extensions for CVIPtools. Partek (7) pattern recognition software was used to analyze the data, to determine the best features and to explore the best statistical model.

Methods

The principal components transform (PCT)/median segmentation algorithm was used to segment the image, followed by morphological filtering to simplify objects. Binary and color features were extracted from the relative color images of skin lesions, which are used to classify the skin lesions. Features from these filtered, segmented objects within the image were extracted to create data models.

Two different feature spaces, lesion feature space and object feature space, were designed and served as the data models in order to maximize the possibility of success. For the two data models, principal components analysis (PCA) and variable selection, discriminant analysis (DA) and the multi-layer perceptron tools were used to determine the best features and explore the best result. Numerous experiments were performed by varying the many available parameters, and the key results are reported here.

To train and test the limited number of skin lesion image samples, the leave-one-out and leave-10-out methods were used to create classification models. The multi-layer perceptron showed marginally higher classification rates than the DA models with successful rates for melanoma as high as 86%. The best overall rates were achieved with the multi-layer perceptron by using the PCA projection data with a hidden sigmoid layer and a softmax output layer.

Creation of relative color images

A skin lesion image consists of skin, lesion and some other noise such as hair and extraneous artifacts. Different people have different skin color tones. The photographic film from which images are processed plays a vital role in the color of the image. All these facts suggest that the absolute color of the lesion does not seem very useful for the research. Hence, a relative color concept was developed 1) to equalize any variations caused by the lighting, photography/printing or digitization processes, 2) to equalize variations in normal skin color between individuals and 3) because the human visual system works on a relative color system (8).

Therefore, the relative color images were created and used in all the analysis and experiments performed to develop the classification models (10). The steps involved in creating relative color images are as follows:

1. Shown in Fig. 1, a non-skin algorithm based on heuristics was performed on the original image to eliminate the extra artifacts such as hair, clothing, teeth rulers, shadows and reflections (11). Then a binary border image of the lesion was used to mask out the lesion. This leaves only normal skin for calculation of the average R, G and B pixel values of the normal skin color.
2. Shown in Fig. 2, the lesion image is created by performing the logic and operation of the border image directly with the original noisy skin lesion image.
3. Shown in Fig. 3, the relative color image of the lesion is created by subtracting the average R, G, and B pixel values of the normal skin from the corresponding R, G and B pixel values of the lesion image.

Segmentation and morphological filtering

The relative color skin lesion images were segmented to find regions that represent objects or meaningful parts of objects (6). After much experimentation, it was determined that the PCT/median split segmentation algorithm (6) performed the best on those images. Figure 4 shows a segmented skin lesion image.

If the image is segmented with more colors, then more details in the image are retained. Experimentally and according to previous research (12), it was determined that using five colors was optimum segmentation; using five colors retains information of most of the features and does not overly complicate the algorithm.

After segmentation, morphological filters were used. First, a morphological opening filter with a circular kernel whose kernel dimension size is five was used as shown in Fig. 5. After

this step, a morphological closing filter with the same kernel type and dimension was used as shown in Fig. 6. Morphological filters were used to reduce the number of objects in the segmented image (6, 13).

Feature extraction

Feature extraction is necessary to simplify the raw image data into higher level, meaningful information (6,14). Feature vectors are a standard technique for classifying objects, where each object is defined by a set of attributes in a feature space. A feature vector is an n -dimensional vector, which contains the measurements of the selected features corresponding to objects of interest in the image.

Histogram features, that is, color features, were extracted in each color band from relative color image objects obtained after segmentation and morphological filtering, along with the binary features area and thinness (6). The three largest objects, based on the binary feature 'area', were used in feature extraction.

Histogram features are statistically based, where the histogram is used as a model of the probability distribution of the color intensity levels. These statistical features provide us with information about the characteristics of the color intensity level distribution for the image or sub image. The features based on the first-order histogram probability are the mean, standard deviation, skew, energy and entropy (6).

The specific 17 features extracted by using CVIPtools software were the following (6):

1. *Area*, which indicates the area of the object.
2. *Thinness*, which indicates the measure of roundness.
- 3, 4, 5. *Mean*, which indicates the brightness of the image in the red, green and blue bands, respectively.
- 6, 7, 8. *Standard Deviation*, which indicates the contrast of the image in the red, green and blue bands, respectively.
- 9, 10, 11. *Skewness*, which indicates the asymmetry about the mean in the intensity-level distribution in the red, green and blue bands, respectively.
- 12, 13, 14. *Energy*, which indicates how the intensity level is distributed in the red, green and blue bands, respectively.
- 15, 16, 17. *Entropy*, which indicates how many bits are needed to code the image data in the red, green and blue bands, respectively.

Two feature spaces setup

For the purpose of experimentation and in order to maximize the possibility of success, we have created two different feature spaces: lesion feature space and object feature space. The object feature space required a minimum object size for selection, and had 842 feature vectors corresponding to the 842 selected image objects. The selected image objects are the two or three largest objects within each skin lesion image. Each feature vector has 17 feature elements, which were the binary features and color features as stated above. The lesion feature space consists of 277 feature vectors corresponding to the 277 selected skin lesion images; images with only two objects were not used for the lesion feature space experiments. Each feature vector has 51 feature elements, which are the total of 17 features of each three largest objects within the same lesion.

Establishing statistical models

Two classification models, DA and multi-layer perceptron, were developed for both feature spaces. Partek software was used to analyze the data representing the features and also to develop a model or rules to classify the lesions.

DA—Quadratic DA is a statistical pattern recognition technique based on Bayesian theory (14), which classifies data based on the distribution of measurement data into predefined classes. The class of an observation is determined based on a set of variables known as predictors or input variables. It takes all the features into consideration and works out which combination of the features is a better predictor of the class to which the object belongs. It divides the feature space using quadratic curves. The model is built based on a set of observations for which the classes are known.

In this project, some dominant features were first selected by the variable selection method because, even though a large number of independent variables (features) are available for a given modeling problem (classification of lesions), not all of these predictor variables contributed equally well to solve the modeling problem. Some of the independent variables (features) did not contribute at all to the model. Thus, we had to select from these variables (features) to obtain a model that contained as few variables as possible while still being the 'best' model.

Normalization of feature data: Data normalization is performed to maximize the potential of the features to separate classes and to satisfy the requirement of the modeling tool such as quadratic DA for a Bayesian distribution of the input data (14). A normalization method was chosen for each feature based on the type and degree of skew in the feature's data distribution (histogram). In our experiments the histogram of the features were manually examined and the best normalization technique was experimentally determined.

Upon observing the histograms of each feature, it was found that many of the features were skewed. The best normalization method for skewed variables was log scaling (base=10), as this will tend to stretch the distribution. A set of normalization methods was used to normalize the feature data representing image objects based on the experiments.

Histograms for feature data for the features area, standard deviation, and energy were skewed. To correct this skew by making the data distribution more Gaussian, the log-scaling (base=10) method was applied. The distributions for the features mean and entropy were normalized by using zero mean and standard deviation as 1, because the original data histograms appeared Gaussian. The feature data for thinness and skewness were skewed, and the data were squared to normalize, and then log scaling (base=10) was applied on the data.

Multi-layer perceptron (MLP)—Neural networks are modeled after the nervous system in biological systems, and based on the neuron as the processing element (6). MLP (15) are feed-forward neural networks (all connections are from input to output, i.e., there is no feedback path). These networks are trained with a training algorithm. These networks require a desired response in order to be trained and so they are called supervised networks. They are widely used for pattern classification, as they learn how to transform the given data into a desired output.

Normalization is not required for the use of the MLP module as in case of DA, as the data will undergo PCA, which will normalize the data.

PCA: PCA, a popular multivariate technique, reduces the dimensionality of P multi-attributes to two or three dimensions. PCA (16, 17) summarizes the variation in a correlated multi-attribute to a set of uncorrelated components, each of which is a particular linear combination of the original variables. The extracted uncorrelated components are called principal components (PC) and are estimated from the eigenvectors of the covariance or correlation matrix of the original variables. Therefore, the objective of PCA is to reduce dimensionality by extracting the smallest number of components that account for most of the variation in the original multivariate data and to summarize the data with little loss of information (18).

The dispersion matrix selected for PCA in this project is correlation, as it gave better results than the remaining matrices (covariance, sum of squares, and sum of products). The results from PCA are inserted into a separate spreadsheet for use by an MLP module.

Creation of neural network: For MLP, first, a network should be created, then trained and then it should be tested for accuracy. The creation of a neural network involves selection of hidden and output neuron types and a random seed for random number generation. There are four output neuron types (softmax, Gaussian, linear and sigmoid) and three hidden neuron types (sigmoid, Gaussian and linear). These neuron types represent the activation function (17, 19) being used.

Sigmoid contains a logistic curve as an activation function, and the output lies in the range of 0 and 1. Softmax uses an exponential function, with results normalized so that the sum of activations across the layer is 1.0. Gaussian uses a combination of negative exponential and radial synaptic functions as its activation function.

Training of neural network: After the network is created, it needs to be trained on the data using a learning algorithm. There are two learning algorithms provided in the Partek software. They are the back propagation and the Scaled Conjugate Gradient (SCG) algorithms. For this project, the SCG algorithm is used for learning because the back propagation algorithm is usually not best for a large set of data; moreover, the success of the back propagation algorithm depends on user-dependent parameters, such as learning rate and momentum constant, whereas SCG is automated and independent of user parameters, and it avoids a time-consuming line search per learning iteration as required by the back propagation (BP) algorithm for each iteration in order to determine an appropriate step size (20).

After the SCG is chosen for training, a stopping criterion is selected. The stopping criterion determines after how many iterations the training should be stopped. This usually depends on the sum-squared error (actual output minus desired output). Training should be performed until the error decreases to a minimum value. This minimum value was observed manually to determine the point where the error stopped going down and became constant. At this point, the training can be stopped.

Testing of neural network: The trained data are then tested on itself first to examine how well the neural network is able to classify the objects correctly. Usually the testing should be performed separately on a test set. But there is a cross-validation option available in Partek. Cross-validation will divide the data set into a specified number of partitions and then all but x of the partitions will be trained using the chosen training algorithm, leaving x partitions out for testing the algorithm. This process continues for all the partitions and the average of all the results will be reported. This is the most accurate testing that is possible.

Experiments and Data Analysis

Training and test paradigm

The training and test paradigm is used in statistical analysis to report unbiased results of a particular algorithm. A training set is used for training or developing the algorithm, and the test set is used for testing the algorithm. Owing to the small size of the data set, we used the leave- x -out method, with both one and 10 for x . In the leave-ten-out method, 10 samples from a data set of N samples are saved for testing and an algorithm is developed based on the remaining $(n-10)$ samples. The ten samples that were withheld are then tested. This procedure is repeated for $n/10$ iterations, with each iteration using $n-10$ samples for developing the algorithm and with the testing performed on 10 remaining samples, which are not used in the training set ($n-10$). The leave-ten-out method was preferred over the leave-one-out method because it requires fewer computations to develop a classification model.

Lesion feature space

DA—At first the leave-ten-out method, which was used to develop a model with fewer computations to classify the lesions, was performed with a data set consisting of 23 features selected via the variable selection method. DA on the complete set of histogram features was performed.

At the beginning, we chose the three largest objects from each lesion as the representative for the lesion. Hence, a total of 51 features from the three largest objects are regarded as the features for the lesion. After variable selection, features for object1 were selected as the histogram means for all three bands, the standard deviation for the red and green bands, and the histogram skewness for the green band, the histogram energy for the blue band and the histogram entropy for the green band of object1. Features for object2 were selected as the histogram mean for the green band, the standard deviation for the blue band, and the histogram skewness for the red and green bands, the histogram energy for the green band, and the histogram entropy for the green and blue bands. Features for object3 were selected as the histogram mean for the green and blue bands, the standard deviation for the red and green bands, and the histogram skewness for the red and blue bands, the histogram energy for the green band and the histogram entropy for the green band. The three objects were placed in the lesion feature vector entry in increasing order of their size. The features selected are marked with an 'x' in Table 1 for easy comparison.

Table 2 shows the success percentages for DA using the leave-ten-out method on data with the above-selected 23 features.

Next, the leave-ten-out method was performed on the data set with 10 features selected via the variable selection method. Features for object1 were the histogram mean for the red and green bands, and the histogram entropy for the blue band. Features for object2 were the histogram mean for the red band, the standard deviation for the red and green bands, and the histogram entropy for the blue band. Features for object3 were the histogram mean for the green band, the standard deviation for the red band and the histogram entropy for the green band. These features are marked with an 'x' in Table 3 for easy comparison. Success percentages for classifying lesions using DA on this data set are listed in Table 4.

The results from the above analysis show a good improvement in classifying dysplastic nevi lesions compared with the analysis performed on a data set with 23 features. This model also shows about a 5% increase in success percentages in classifying dysplastic and nevus lesions compared with the leave-one-out method shown in Fig. 7 at the expense of missing more melanomas.

MLP using PCA projection data—PCA was performed on the complete feature set, but excluding the area and thinness features. Because the multi-layer perceptron is a neural classifier, the input layer takes the PCA projection. The input layer passes the knowledge of the input attributes to the hidden layer for processing. As the best features occur in the first three components of the PCA projection data, no other variable selection method was required. Only the first three components of PCA projection were used. Numerous experiments were performed by varying the number of hidden layers, the types of neurons, and the number of training iterations. Figure 8 represents the best results obtained and Table 5 lists the best result among them.

Using sigmoid hidden layer and softmax output layer over 700 iterations—MLP was performed on PCA projection data using the hidden sigmoid layer and a softmax output layer for 700 iterations. Success percentages of melanoma as high as 77% and of nevus as high as 68% were obtained as shown in Table 5. This shows an increase in nevus and dysplastic success percentages compared with DA on PCA projection data.

Object feature space

DA—After the feature data were normalized, variable selection was used to select some significant features and DA was performed on the filtered data. Now the cross-validation option is used and data are partitioned into 842 partitions. All partitions but one will be trained, leaving one partition out for testing.

Table 6 lists all the eight, nine, 11 and 12 significant features selected, respectively, for leave-one-out method for an easy comparison.

Table 7 shows the best result obtained by using the DA method for the classification of data using the 11 most statistically significant features. These features were determined by using the variable selection method. The features are area, mean in the red, blue and green bands, standard deviation in red and green bands, histogram skewness in the three bands and histogram entropy in the red and blue bands.

Figure 9 shows the results of DA with eight, nine, 11 and 12 significant features selected via variable selection in object feature space.

MLP using PCA projection data—Numerous experiments were performed to select different combinations of neuron types for hidden and output layers. Because there are three hidden layer neuron types, and four output layer neuron types, 12 combinations are possible. But of all the 12 combinations, only five combinations gave better classification results. The five hidden–output layer neuron combinations are (1) sigmoid–sigmoid, (2) Gaussian–Gaussian, (3) Gaussian–linear, (4) Gaussian–softmax and (5) sigmoid–softmax.

The cross-validation option is used for testing the model by partitioning the data into 842 partitions. All partitions but one are trained, leaving one partition out for testing.

Table 8 shows the results obtained by using the multi-layer perceptron for the classification of data using 130 as the maximum number of iterations. The neuron types used are sigmoid for both the hidden and output layers.

Table 9 shows the results obtained by using an MLP module for the classification of data using maximum iterations of 425. The neuron types used are Gaussian for both the hidden layer and output layer.

Table 10 shows the results obtained by using the MLP module for the classification of data using a maximum number of iterations of 255. The neuron types used are Gaussian for the hidden layer and linear for the output layer.

Table 11 shows the results obtained by using the MLP module for the classification of data using a maximum number of iterations of 700. The neuron types used are Gaussian for the hidden layer and softmax for the output layer.

Table 12 shows the results obtained by using the MLP module for the classification of data using a maximum number of iterations of 130. The neuron types used are sigmoid for the hidden layer and softmax for the output layer.

MLP analysis has yielded a success percentage as high as 86% for classifying melanoma. The MLP is more consistent in classifying melanoma and also nevus skin lesions as shown in Fig. 10.

Conclusions

Summary and further research

Based on the results from both the lesion feature space and the object feature space, the MLP with feature data preprocessed by PCA gave better classification results than DA. The best classification results are achieved with sigmoid used as the hidden and output layer neuron type for the MLP with PCA on the object feature space. It gave the best overall success rate of 78%, with 86% correct melanoma classification, 72% correct nevus classification and 56% correct dysplastic nevi classification. This means that the MLP on PCA data using sigmoid as the hidden and output layer neuron type is a better model for classifying the different skin lesions. We successfully classified 86% of malignant melanoma within the database, an accuracy comparable with the clinical accuracy of dermatologists.

Comparing the two feature spaces, the success rates using MLP with PCA as preprocessing on both of them are similar. This suggests that either the lesion feature space or object feature space are good relative color feature spaces for establishing a statistical model to differentiate the malignant and benign skin lesions. It also implies that the three largest lesion objects are representative of the whole skin lesion.

Also, from the variable selection and DA results, we think the features area, mean in the red and blue bands, standard deviation in the red and green bands, skewness in the green band as well as entropy in the red band are the best color features to differentiate the various lesions.

However, the misclassification of a small percentage of melanoma, as well as the relatively low success rate for nevus and dysplastic nevi suggests that we may not have a complete data set for the experiments. Therefore, in order to achieve better classification results, future experiments need a more complete skin lesion image database.

It would be a good idea to combine the relative color features and texture features for future research. By combining the color and texture features, we believe that a more complete feature space will allow for a better differentiation and yield productive results.

Use of the newer dermoscopy images (21) is another approach that should be explored for development of a better solution for detecting the deadly melanoma skin lesions. Dermoscopy is a simple technique that enables detailed examination of the structure of pigmented skin lesions. Dermoscopy images contain visual information that cannot be seen in the clinical images and provide much greater detail of structure within the skin lesion.

This enables significant improvement of diagnosis so that dermatologists favor these specialized images as a diagnostic aid.

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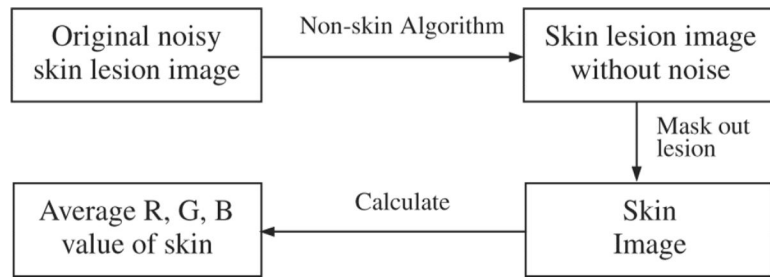


Fig. 1. Calculate the average value of skin color.

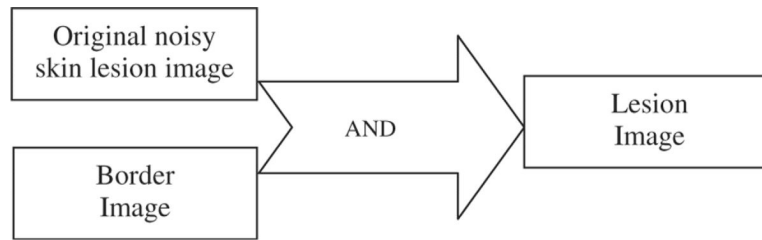


Fig. 2.
Lesion image.

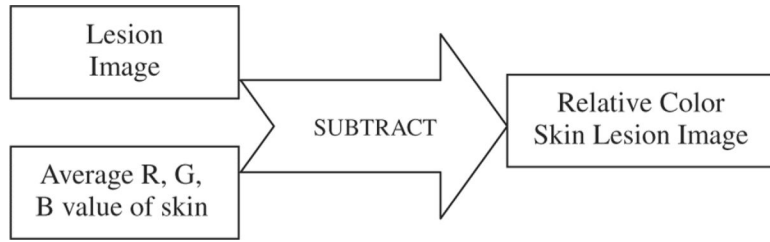


Fig. 3.
Relative color image of the skin lesion.

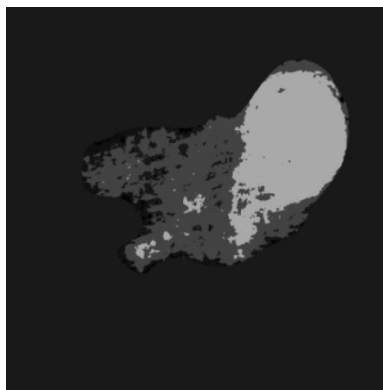


Fig. 4.
Principal components transform /median segmented image.



Fig. 5.
Image after opening (morphological filter) was applied.

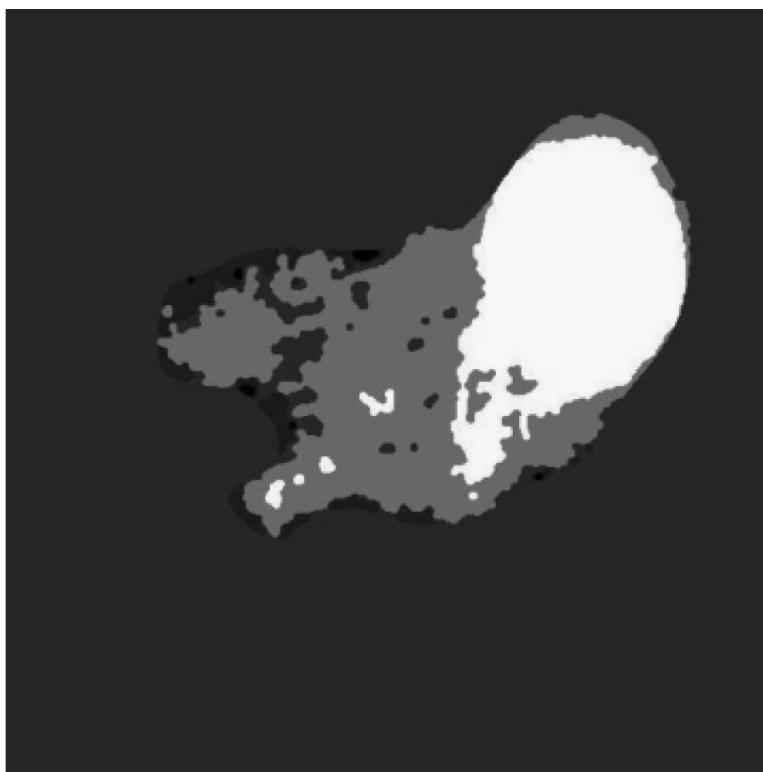


Fig. 6.
Image after closing (morphological filter) was applied.

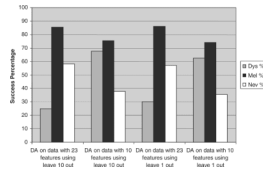


Fig. 7.
Result of discriminant analysis (DA) in lesion feature space.

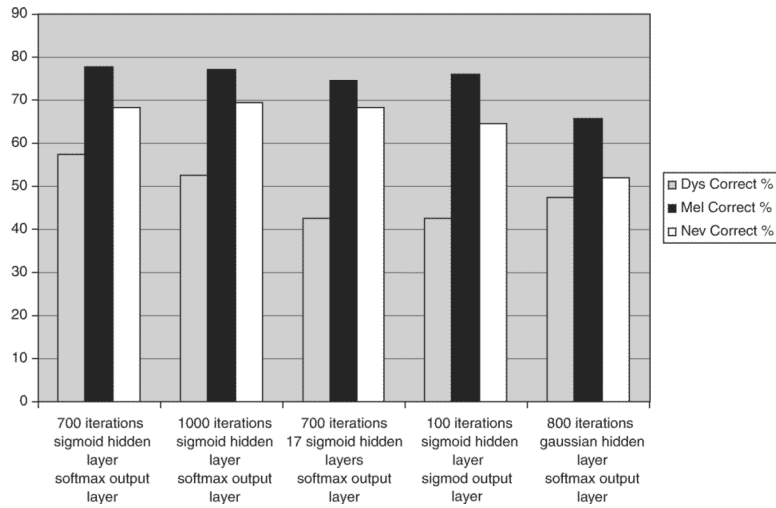


Fig. 8. Result of multi-layer perceptron analysis using the principal component analysis projection data in lesion feature space.

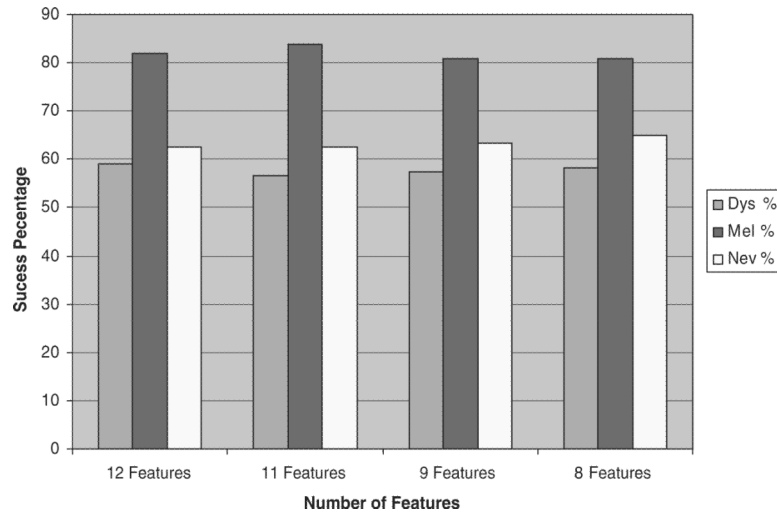


Fig. 9. Result of discriminant analysis in object feature space.

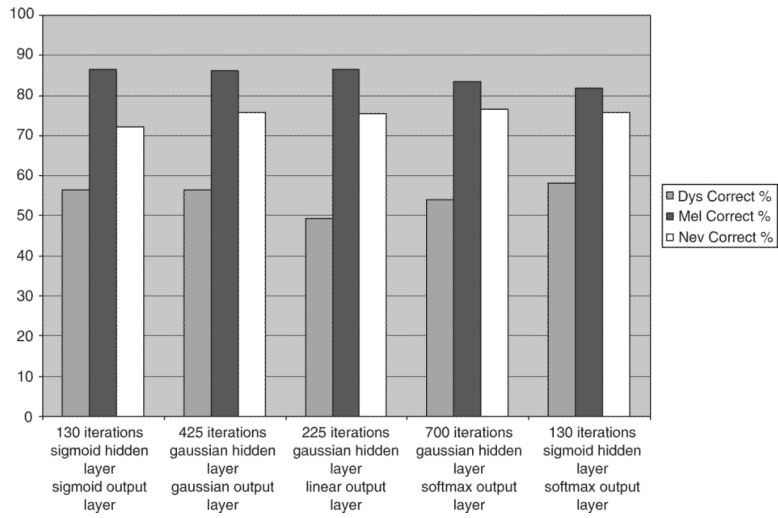


Fig. 10. Result of multi-layer perceptron analysis in object feature space.

TABLE 1

Twenty-three features selected via variable selection method

Histogram features	Area	Thinness	Mean			STD			Skewness			Energy			Entropy		
			R	G	B	R	G	B	R	G	B	R	G	B	R	G	B
Object1		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Object2			x				x			x				x			x
Object3				x				x			x				x		

TABLE 2

Classifying summary for discriminant analysis on using leave-10-out method data with 23 selected features

	# per class	# correct	t # errors	% Correct	% error
Dys	40	10	30	25.00%	75.00%
Mel	158	135	23	85.44%	14.56%
Nev	79	46	33	58.23%	41.77%
Total	277	191	86	68.95%	31.05%

TABLE 3

Ten features selected via variable selection

Histogram features	Area	Thinness	Mean			STD			Skewness			Energy			Entropy			
			R	G	B	R	G	B	R	G	B	R	G	B	R	G	B	
Object1			x	x													x	
Object2			x				x	x										x
Object3					x				x									x

TABLE 4

Classifying summary for discriminant analysis using leave-10-out method on data with 10 selected features

	# per class	# correct	# errors	% correct	% error
Dys	40	27	13	67.50	32.50
Mel	158	119	39	75.32	24.68
Nev	79	30	49	37.97	62.03
Total	277	176	101	63.54	36.46

TABLE 5

Classifying summary for MLP analysis on PCA projection data over 700 iterations using sigmoid hidden layer and softmax output layer

	# per class	# correct	# errors	% correct	% error
Dys	40	23	17	57.5	42.5
Mel	158	123	35	77.85	22.15
Nev	79	54	25	68.35	31.65
Total	277	200	77	72.2	27.8

MCP, multi-layer perceptron; PCA, principal component analysis.

TABLE 6

Eight, nine, 11 and 12 features selected, respectively, for leave-one-out method

Number of histogram features	Area	Mean			STD			Skewness			Energy			Entropy		
		R	G	B	R	G	B	R	G	B	R	G	B	R	G	B
8	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
9	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
11	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
12	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

TABLE 7

Classifying summary for discriminant analysis on data with 11 features

	# per class	# correct	# errors	% correct	% error
Dys	122	69	53	56.56	43.44
Mel	472	395	77	83.69	16.31
Nev	248	155	93	62.50	37.50
Total	842	619	223	73.52	26.48

TABLE 8

Results obtained by using MLP module with sigmoid neurons for hidden and output layers

	# per class	# correct	# errors	% correct	% error
Dys	122	69	53	56.56	43.44
Mel	472	408	64	86.44	13.56
Neu	248	179	69	72.18	27.82
Total	842	656	186	77.91	22.09

Maximum number of iterations 130.

MCP, multi-layer perceptron.

TABLE 9

Results obtained by using MLP module with gaussian neurons for both hidden and output layers

	# per class	# correct	# errors	% correct	% error
Dys	122	69	53	56.56	43.44
Mel	472	407	65	86.23	13.77
Neu	248	188	60	75.81	24.19
Total	842	664	178	78.86	21.14

Maximum number of iterations 425.

MCP, multi-layer perceptron.

TABLE 10

Results obtained by using MLP module with Gaussian Neurons for the hidden layer and linear neurons for the output layer

	# per class	# correct	# errors	% correct	% error
Dys	122	60	62	49.18	50.82
Mel	472	408	64	86.44	13.56
Neu	248	187	61	75.40	24.60
Total	842	655	187	77.79	22.21

Maximum number of iterations 225.

MCP, multi-layer perceptron.

TABLE 11

Results obtained by using MLP module with Gaussian neurons for the hidden layer and softmax neurons for the output layer

	# per class	# correct	# errors	% correct	% error
Dys	122	66	56	54.10	45.90
Mel	472	394	78	83.47	16.53
Neu	248	190	58	76.61	23.39
Total	842	650	192	77.20	22.80

Maximum number of iterations 700.

MCP, multi-layer perceptron.

TABLE 12

Results obtained by using MLP module with SIGMOID neurons for the hidden layer and softmax neurons for the output layer

	# per class	# correct	# errors	% correct	% error
Dys	122	71	51	58.20	41.80
Mel	472	386	86	81.78	18.22
Neu	248	188	60	75.81	24.19
Total	842	645	197	76.60	23.40

Maximum number of iterations 130.

MCP, multi-layer perceptron.