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Skin Cancer Detection Using Support Vector Machine Learning Classification based on Particle Swarm Optimization Capabilities

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ABSTRACT

Skin cancer continues to be a common malignancy that has steadily increased each year. The need for early detection of such skin lesions is critical to preventing further medical complications. The main method for detection of skin cancer is by microscopic examination of skin lesions. Great efforts have been placed to use computer aided technologies for the analysis of skin lesions. In this study, we present a method for an algorithm design using Support Vector Machine (SVM) learning classification based on Particle swarm optimization (PSO) principles in order to improve the accuracy of skin lesion image analysis and classification for further diagnosis. Hospital Pedro Hispano (PH^2) dataset with 200 images is used for this study. The method presented here incorporates 46 texture features in order to complete comprehensive image analytics and classification. The proposed method demonstrates an opportunity to explore best possible criteria in image analytics for clinical decision support.

Keywords: Skin cancer detection; Melanoma; Benign; Particle swarm optimization (PSO); Image feature extraction; Support vector machine (SVM).

1 Introduction

Skin cancer continues to be classified as a very common malignancy by the American Cancer Society [1]. More cases of skin cancer are diagnosed each year than all other cancers combined [2]. In general, skin cancer can be classified as a melanoma, which is malignant, or non-melanoma skin cancer. Classification of the benign non-melanoma skin cancer includes either basal cell or squamous cell carcinoma types [3]. Application of machine-learning image analytic algorithm is investigated in this study for skin image analysis to more accurately detect and diagnose melanoma lesions.

1.1 Skin Cancer.

The Center for Disease Control tracks melanoma type of skin cancer with national cancer registries, and the data show that in 2014 there were 76,665 people diagnosed with melanomas in the United States [4]. More specifically, of those diagnosed, 9,234 patients died from melanoma in 2014. Since the early 1970s, malignant melanoma incidence has risen. For example, in the USA, it increased by about 4 percent every year [4]. Experts suggest that the increased incidence is related to the fact that about 90% of melanomas are linked to severe ultraviolet rays (UV) exposure and sunburns over a lifetime [5]. Additionally, diagnosis

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at early stages is essential since delayed diagnosis of melanoma can have a negative impact on 5-year survival rate and increased treatment cost [6]. The estimated 5-year survival rate for melanoma cancers is typically 99% if detected in the early stages of the disease, but decreases to approximately 14% if cancer detection is made in later stages.

1.2 Related Work.

Accurate diagnosis of melanoma can be a challenge with lesion imaging tools such as the standard dermatome scanner. Additional diagnostic methods include histological image analysis following invasive skin lesion biopsy and microscopy techniques. Overall, the precision of melanoma diagnosis by experts is within 75%–84%. This emphasizes the need for innovative tools in diagnostics methods such as computer-based analysis of skin cancer-related images [7].

In spite of efforts to develop lesion image data analysis with Artificial Intelligence (AI) capabilities, analytic software has not been able to fully replicate human analysis [8]. Advanced computational analysis with machine learning methodologies are being investigated to develop algorithms, which can identify clinical characteristics in skin lesion images that might be missed by human observation [9]. Therefore, diagnostic image processing and analysis by computer-aided systems can play an essential role in the clinical domain.

Humans can classify objects easily such as medical images from various patients, but this task is complex for computers and is dependent on accurate reference databases to train analytical behaviors. Numerous techniques have been investigated for machine learning which requires the classification of images with identification labels being assigned to the sections of the image to achieve object classification and feature extraction. Typically, computer based image classification systems are developed with a defined database of images that includes predefined patterns in order to classify a detected object in the proper disease category [10].

Earlier studies in image identification such as by Bono et. al. [11], described a clinical study of 22 cases of melanoma with the diameter of less than 3 mm. In their work, they noticed that the commonly used Asymmetry, Border, Color, Diameter (ABCD) guide [11] for diagnostic algorithm becomes redundant while evaluating micro-melanomas and that traditional dermoscopic diagnostic methods often fail. Meanwhile, Al abbadi et. al. [12], proposed a method for skin texture recognition using both color and texture features of lesions and image classification using three layer neural networks. In an attempt to assist non-experts in clinical diagnosis, the fuzzy logic analytic engine was tested to classify image objects based on both its Euclidean and fractal geometric properties in skin cancer images [13].

This study is attempting to investigate and validate a proposed machine learning algorithm for skin cancer detection with integration of image segmentation techniques based on Support Vector Machine (SVM) as a supervised learning model for the algorithm which is refined with Particle Swarm Optimization (PSO) in order to achieve accurate classification of the images.

2 Methodology

In this study, the main principles applied to classify skin lesion images are Support Vector Machine (SVM) classification algorithms based on initial image segmentation using Particle Swarm Optimization (PSO).

2.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is one of optimization techniques with applications in very broad fields [14 - 16]. The PSO model is developed on principles of swarm intelligence and is a powerful tool for sorting best solution within a population of data sets under specific situations with fast execution time. The image pixels (particles) are analyzed iteratively through the d-dimension problem space to search for the new solutions, where the fitness f can be calculated as certain qualities are measured. Each particle has a position represented by a position-vector xi (i is the index of the particle) and a velocity represented by a velocity-vector vi. The algorithm remembers each particle's best position in a detection and its d-dimensional of the image [17].

2.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a machine learning model for linear classifier of images following a supervised learning method for classification and regression prediction. This statistical learning theory provides a mechanism for supervised machine learning from a defined set of data. Its advantage is in greater ability to generalize statistical learning and was validated [18], to classify melanocytic lesions into malignant or benign categories from dermoscopic images. Safi et al. [19], used SVM classifier on capillary detection in the skin cancer images. They estimated the likelihood of capillaries based on the distance to the red color in the "CIE Lab" color space. Uzmabano Ansari and Tanujasarode [20], proposed a skin cancer detection system using SVM for early detection of skin cancer disease. The image was analyzed by its features using Gray Level Co-occurrence Matrix (GLCM) methodology. These image features serve as the input to the classifier software and SVM was used for image classification into cancerous or non-cancerous categories. These studies demonstrate that SVM can be used in bioinformatics because of better empirical performance, its ability to process high-dimensional data, and flexibility in modeling different kinds of data.

In this study, we utilize principles of non-linearly separation of original input space, and generate nonlinear classifiers using kernel functions [21]. Thus, computational analysis of the features in images along vectors is better achieved with kernels as an alternative approach.

2.3 Overall Image Analysis Methodology

The proposed technique of skin lesion image processing with sequential analytic stages is summarized in Figure 1. Initial image acquisition is the foundation data, followed by image preprocessing and then segmentation of the image, using particle swarm optimization (PSO) as an intelligent tool for detecting the region of interest (ROI). The image features in the image such as geometric, color, and texture are then extracted from the defined ROI for lesion classification. Utilizing image normalization and selection, the next stage involves image classification of features using a support vector machine (SVM) prior to eventual clinical diagnosis.

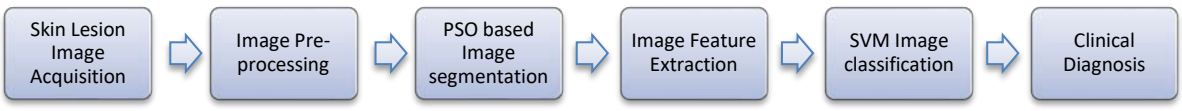


Figure 1. Image analysis layout.

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2.3.1 Image Acquisition

Skin lesion images are typically captured by dermoscopes. The images for this study come from the Hospital Pedro Hispano (PH^2) dataset [22]. Two hundred dermoscopy images of PH^2 were analyzed to detect melanoma lesions using software code written in MATLAB. This dataset consists of 80 common nevi, 80 atypical nevi, and 40 melanomas. Medical annotation of all the images, namely medical segmentation of the lesion, clinical and histological diagnosis and the assessment of several dermoscopic criteria, are included in the PH^2 dataset. These dermoscopic criteria are comprised of colors, pigment network, dots/globules, streaks, regression areas and blue-whitish veil.

2.3.2 Image Preprocessing

The proposed cancer detection method starts by preprocessing the skin lesion image using PSO as a segmentation tool from two groups of skin images, benign and melanoma. The aim of preprocessing is to improve the image data analysis such that there is suppression of undesired distortions in the image and enhances some image features relevant for further processing and the analysis task [23, 24]. This image enhancement adjusts the image so that critical visual information can be viewed and assessed with greater clarity by computer algorithms. After reading the colored image from the dataset, the image is split into its three main color bands (Red, Green, and Blue). Then a median filter with the size of (3*3) is applied on each color band to remove background noise in the images and provide enhancement. Three morphological masks at zero, 45, and 90 degrees are applied using a morphological close function with the following equation,

$$A \bullet B = (A \oplus B) \ominus B$$

The equation shows that the closing of a set (binary image) *A* by a structuring element *B* is the erosion of the dilation of that set; where $\oplus$ and $\ominus$ denote the dilation and erosion, respectively. This closing process is a dilation followed by an erosion, that merges narrow breaks or gaps and eliminates small holes. The three results from the three masks are gathered as one output to replace the input image. Additionally, a Gaussian filter was applied using the following equation:

$$f(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

where the filter size is (3*3) pixels and the coefficient sigma is equal to 1.1

2.3.3 Image segmentation

2.3.3.1 Particles Swarm Intelligent (PSO)

The lesion area is digitally separated from healthy skin using image segmentation. The PSO tool is used to perform image segmentation and optimization of the image. Basic PSO model is an intelligent search method for each pixel in the skin image using a population of artificial particles. Classes of pixels are assigned values for each particle iteratively depending on the fitness function. Practically, the maximum moving distance during one iteration is clamped between [-5, 5]. Random numbers (r1 and r2) are between [0, 1].

The first equation determines the new position xi (t+1) for each particle in order to find the best position.

$$xi\ (t+1) = xi\ (t) + vi\ (t+1)$$

where, xi and vi are the initial position and the initial velocity, respectively. The second equation defines the new velocity vi (t+1) which is needed in the previous equation.

$$vi\ (t+1) = w * vi + c1 * r1 * (pi\ (t) - xi\ (t)) + c2 * r2 * (g(t) - xi\ (t))$$

where, w is the inertia term and c1 is the coefficient of the self-recognition component, c2 is the coefficient of the social component and r1, r2 are the random numbers, which are used to maintain the diversity population, and they are uniformly distributed in the interval [0,1]. The pi is the best personal position-vector, which each particle has and remembers. Meanwhile, g(t) is the best position-vector among the swarm. Therefore, the term (c1 *r1* (pi (t)) is for exploring and diverging for each particle, called self-recognition term. In contrast, the (g(t) - xi (t)) is for converging in order to find the best position-vector among all position-vectors, which is called the social term.

The third equation is the fitness function, or the optimization problem, this function is different from one problem to another. In this particular study, the fitness function is the variance of the intensity distributions of skin image between classes.

$$Var = \sum_{j=1}^{n} w_j (\mu_j - \mu_t)^2$$

where, j is a specific class, μ_j is the average of the occurrence of class j, μ_t is the average of occurrence of the whole image and W_j is the probability of occurrence of class j. Maximum variance can be used as a dividing tool for dividing a skin image into two regions based on intensities.

2.3.3.2 Region of Interest Detection

The region of interest (ROI) detection process is based on the PSO segmentation method and is used for localization of image feature extraction. The ROI detection relies on four factors, that are used to determine the differences between the segmented images after using PSO and the ground truth lesion GT (binary image): Hammoude distance (HD), True detection rate (TDR), False position rate (FPR), and Gross error (GE).

Findings from ROI detection are used for the image's feature extraction and lesion border circularity which will be useful for diagnosing and specifying the geometric shape of the lesion.

2.3.4 Image Feature Extraction

Accurate skin lesion image classification depends on extracting relevant features including Geometric Features, Color Features, and Texture Features. Geometric features include the area of ROI, perimeter of ROI, the distance to centroid of ROI and the distance to center of nearest ROI. Color features consist of the mean, standard deviation and variance for each color band of the image. The Texture features involve identifying features extracted from the gray level co-occurrence matrix (GLCM) which includes 19 features. Homogeneity, entropy, energy, dissimilarity and contrast are some of the features extracted by using GLCM. GLCM characterizes the texture and calculates how often a pair of intensity values occur in an image. The gray level run length matrix (GLRLM) is another method that is used for extraction of texture features, which includes 11 additional features.

A total number of 46 features are analyzed for complete image analysis. However, some features of the dataset may have no weight at all or have a high level of noise. Therefore, the Mutual Information (MI)

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method is used to give weight to each feature; these weights then are sorted from high to low. Finally, a selection of a relevant subset of vectors with significant features applied in the training image set criteria are used for image classification.

2.3.5 Image Classification

Classification of the image being analyzed uses the support vector machine (SVM) methodology with both global and local approaches within the ROI. This process uses two kernels, linear and polynomial. The maximization of margins between negative and positive examples depend on SVM.

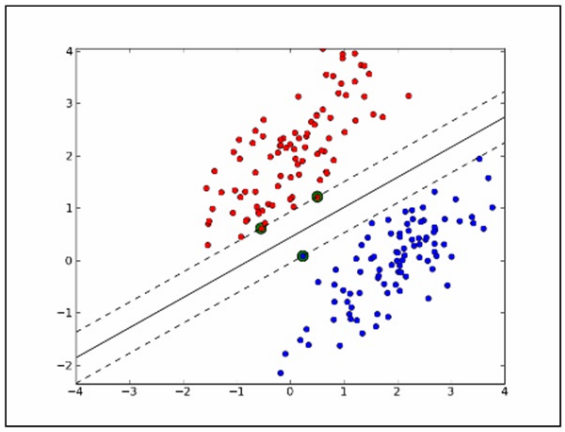


Figure 2 Support Vector Machine

In a case of two classes' problem with N number of training samples as shown in Figure 2, each group of samples is described by a Support Vector (SV) X_i. It is composed of different data (features) with a number of dimensions from each side of the hyperplane. For a case of two classes, the label of a sample is assigned (-1) for the first class's label and (+1) for the other. The SVM classifier consists in defining the function using the following equation:

$$f(x) = sign(\langle w, x \rangle + b)$$

where w is the distance between the hyperplane and the margin which needs to be maximized. w has to be perpendicular to the hyperplane, x is the data (feature), and b is the bias. The sign of f(x) gives the label of the sample whether it is positive or negative.

The goal of the SVM is to maximize the margins between the support vectors and the optimal hyperplane. Therefore, it is easier to use the Lagrange multiplier as in the following equation:

$$f(x) = sign(\sum_{i=1}^{n} y_i \,.\, \alpha i \, \langle x.x_i \rangle + b)$$

where (αi) is the Lagrange multiplier.

Since SVM is a linear classifier, Kernel Trick is used to solve a non-linear problem for image classification. Kernel allows the projection of the initial data in a feature space with higher dimension. The different types of kernels applied in this study include Polynomial kernel, Linear kernel, and Gaussian kernel.

The SVM training model is used for training the machine learning algorithm and confirming capability for predicting the classification of new image samples. After a successful evaluation of the training, the data set is used for testing and then to the validation. This validation of the model is done with cross-validation since this is a resampling process to avoid overfitting image sets for the final evaluation. This involved using a parameter k to represent the number of groups the data sample is divided into. For this study, the training data is divided into N subsets of equal size, creating (N-1) fold groups used as training sets and the one remaining fold as a validating set. In this study, cross-validation implements 5 folds to pursue accurate results. Thus, each instance of the whole training set is predicted once. Consequently, the cross-validation accuracy is listed as the percentage of data which are correctly classified. The average score across all models is considered the final performance of the model. Thus, we report the performance of the model based on the local validation data, derived from the group's average score.

The testing phase classifies each row of the vector of features that is not labeled; while in training the rows are labeled, using the information in a support vector machine classifier structure. Note that the defined image structure is created using the training step. The sample is a matrix of observations where each row corresponds to it or replicates, and each column relates to a feature or variable. Thus, the sample has the same number of columns as the training data. This is because the number of columns defines the number of features.

3 Results

PH^2 data set used in this study includes 200 dermoscopic images of melanocytic lesions and consists of 80 common nevi, 80 atypical nevi, and 40 melanomas. Medical annotation of all the images, namely medical segmentation of the lesion, clinical and histological diagnosis and the assessment of several dermoscopic criteria, are included in the PH^2 database. The dermoscopic criteria are comprised of colors, pigment network, dots/globules, streaks, regression areas and blue-whitish veil. Following the paradigm outlined in Fig. 2 above, image preprocessing is applied to both skin image sets, benign and melanoma.

With image preprocessing stage to separate colors in the original skin images (Fig. 3a) to RGB color bands a median filter was applied on each band (Fig. 3b). Secondarily, morphological closing operation was achieved to the image with line structure element: Horizontal line (zero angle), sloped line (45 angle), and vertical line (90 angle). The outcome from these three bands, maximum values are obtained and the hair area, which is close to dark in color, is replaced. (Fig. 3c) The following application of Gaussian smoothing filter on the result (Fig. 3d) achieved image results that could be subjected to Particle Swarm Optimization (PSO) image segmentation.

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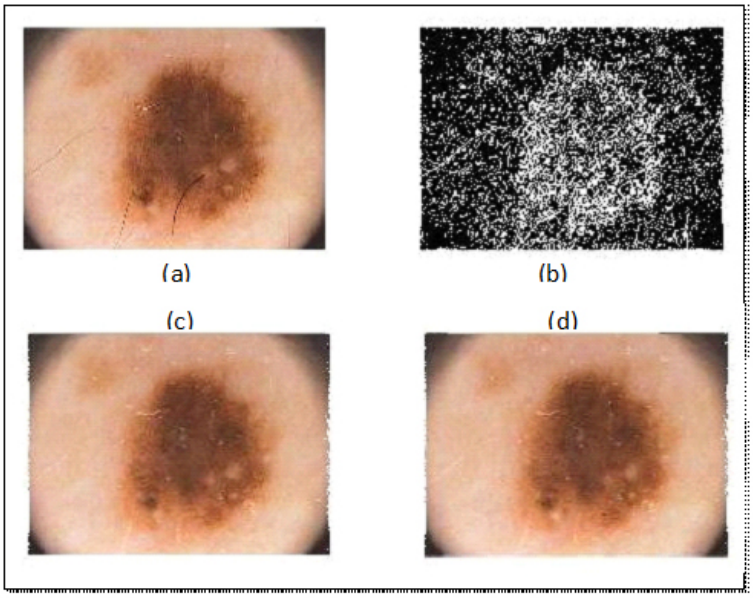


Figure 3. (a) Original Skin Image (b) Image after Splitting and Applying Median Filter (c) Image after Replacing Hair Area (d) Image after Applying Gaussian Filter.

Segmentation achieved effective enhancement of the resulted image by comparing it with ground truth (GT) image of the same lesion. Thus four parameters, Hammoude Distance (HD), True Detection Rate (TDR), False Position Rate (FPR), and Gross Error (GE) achieved computing differences between two images, the ground truth lesion GT (binary image) and image from segmentation method. The outcomes of these parameters are listed below in Table 1 for benign samples and Table 2 for melanoma. These data are used to evaluate the PSO segmentation method.

Table 1. PSO Segmentation Algorithm Evaluation for Benign Samples

Segmentation methods	Datasets (Benign skin cancer images) number of images (160)			
	HD (%)	TDR (%)	FPR (%)	GE (%)
PSO	4.257	97.000	5.225	3.000

Table 2. PSO Segmentation Algorithm Evaluation for Melanoma Samples

Segmentation methods	Datasets (Melanoma skin cancer images) number of images (40)			
	HD (%)	TDR (%)	FPR (%)	GE (%)
PSO	1.018	23.764	0.883	0.000

Following image analysis, the resulted binary image becomes inverted in order to make the white area relate to region of interest (ROI) leading to the identification of ROI. As an example, the resulting outcome from ROI detection, enhanced ROI, and cropped images for benign samples are shown in Figures 4.1, 4.2, and 4.3.

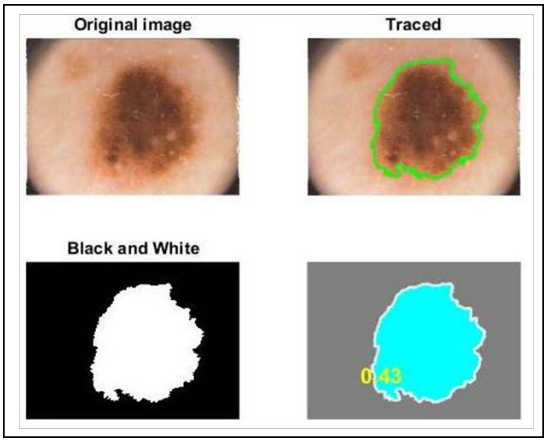


Figure 4.1. ROI Detection using PSO Algorithm (Benign Samples)

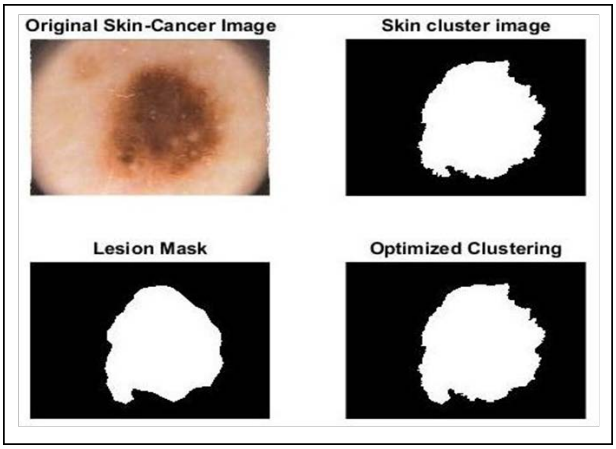


Figure 4.2. Enhancement of ROI (Benign Samples)

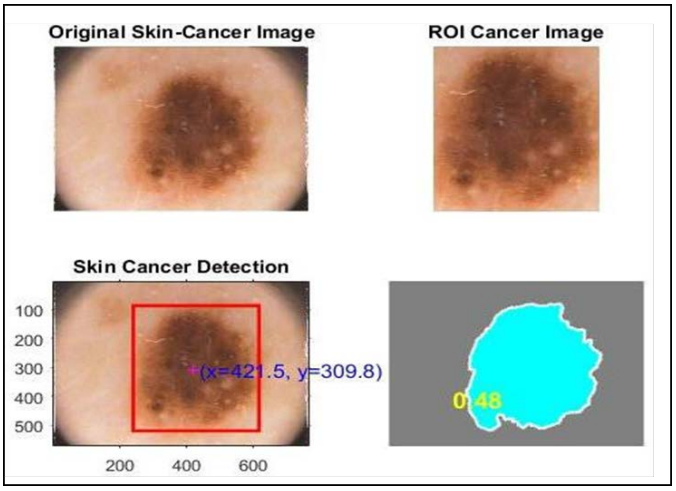


Figure 4.3. Image Crop of ROI (Benign Samples)

Similarly, an example of the resulting outcome from cropped images for melanoma samples is shown in Figure 5.

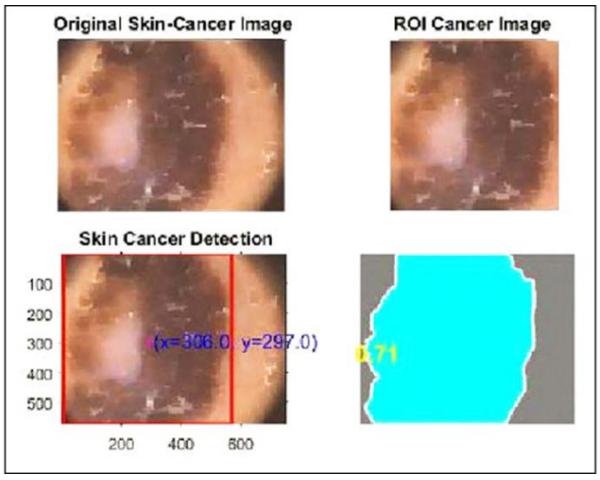


Figure 5. Image Crop of ROI (Melanoma Samples)

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The selected region of interest from each image is used for localized feature extraction process. By using three kinds of features extracted from the images, geometric features, color features, and texture features, a total of 46 features are proposed with this method. Example of first 14 out of 46 features with their associated weights for evaluating a sample image is listed in Table 3.

Table 3. Skin Image Features (feature 1 to feature 14)

Image #	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7
1	6023.88	9910.70	10509.46	123.00	0.00	44383.73	17741.26

Image #	Feature 8	Feature 9	Feature 10	Feature 11	Feature 12	Feature 13	Feature 14
1	168.11	25.89	107.11	23.71	76.11	19.07	1105.59

The next phase involves SVM model's further evaluation with k-fold crosses validation, by subjecting the training image set to split into k smaller sets. That resulted in SVM model to be trained using (k-1) folds one remaining fold as the model validating set. Applying 5 folds of cross-validation is achieved with 24 image features and combinations of 80% training set and 20% testing set, 70% training set and 30% testing set, and finally 75% training set and 25% testing set.

As an example, the outcomes of the cross validation for image # 178 with kernel classification are listed in Table 4 for linear kernel. The data table lists Sensitivity as SE, Specificity as SP and Precision as PPV.

Table 4. Training Linear Kernel

Fold #	Training Fold				Testing Fold
	SE (%)	SP (%)	PPV (%)	Accuracy (%)	Accuracy (%)
fold 1	92.86	100.00	100.00	94.29	97.14
fold 2	100.00	100.00	100.00	100.00	100.00
fold 3	100.00	87.50	96.55	97.22	97.14
fold 4	96.43	100.00	100.00	97.22	97.14
fold 5	100.00	100.00	100.00	100.00	100.00
Cross Validation Time	14.78 Sec				

Similar outcomes for the same image #178 are obtained for polynomial kernel with training fold accuracy ranged from 94.44% to 100%; testing fold accuracy ranged from 94.44% to 100% and cross validation time of 47.85 sec. The outcomes are also obtained for Gaussian kernel with training fold accuracy ranged from 91.67% to 100%; testing fold accuracy ranged from 91.66% to 100% and cross validation time of 17.64 sec.

Following the progression in image analysis, the SVM model performance using all the 46 selected features is tested for accuracy and testing time with linear kernel, polynomial kernel, and Gaussian kernel. The tested results for linear kernel are shown in Table 5.

Table 5. Results of SVM Testing

Globalization	SE (%)	SP (%)	PPV (%)	Accuracy (%)	Testing Time (sec)
Linear kernel	100	100	100	100	0.0298

The same result of Accuracy = 100 % is also achieved for polynomial kernel with testing time of 0.0301 sec. and for Gaussian kernel with testing time of 0.0277 sec. , respectively. When lower number of features in sorting the images is used, the classification accuracy is reduced as anticipated.

4 Discussion

In this study, we have investigated the capability of applying computer based analytics to sort dataset of skin lesion images in order to support clinical diagnostics. The methodologies and associated outcomes presented here validate previous studies testing PSO and SVM as image classification tools. Working with brain MRI images, the hybrid technique using the combination of PSO and SVM achieved a very high accuracy with SE = 97.5% and SP = 100% [25]. Similarly, other studies have applied machine learning to guide clinical opinion and found automated analysis to perform better than clinical review with 100% accuracy [26, 27].

The results obtained from this study also support the study outcome demonstrating that feature extraction plays an important role for image classification. Catarina Barata, et al. [28] showed that the selection of different types of features may lead to different accuracies in lesion classification with the same set of images. JTC Ming, et al. [29] used a deep learning architecture to produce 4096 features and obtained 100% accuracy in computer aided diagnosis for lung disease classification. In their study [29], 79 features were used to achieve 100% accuracy when Principle Component Analysis (PCA) was introduced. In this study, PSO is used for segmentation, SVM is used for classification; and when a total of 46 selected features are used, 100% classification accuracy is achieved.

Since the number of data set in this study is limited, the possible directions for further advances of this study are to include the use of a larger dataset and to investigate the use of different combinations of technologies for segmentation, feature extraction and lesion classification.

5 Conclusion

In this study, a computerized analytic method applying machine learning principles is presented to diagnose melanoma from skin lesion images using the Hospital Pedro Hispano (PH^2) dataset. This method demonstrates the effectiveness of using Particle Swarm Optimization (PSO) for image segmentation and Support Vector Machine (SVM) for classification as well as selection of suitable and sufficient features in image analysis. Furthermore, the final results have demonstrated that the proposed method for the segmentation was robust because the local extracted features from ROI were acceptable. This technique provides high accuracy to support assisting clinicians classifying skin lesion images into relevant diagnostic categories.

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