

GLOBAL PROCESSING SYSTEM BASED SKIN CANCER CLASSIFICATION SING DERMOSCOPIC IMAGES

S. Mohan kumar^{1*} and T. Kumanan²

*1*Research Scholar, Meenakshi Academy of Higher Education and Research, Chennai, India*

mohankumars.phd@gmail.com

*2Professor, Department of Computer Science and Engineering, Meenakshi Academy of
Higher Education and Research, Chennai, India*

kumananvetri@gmail.com

ABSTRACT: *The Global Processing System (GPS) of Non-Subsampled Shearlet Transform (NSST) features for dermoscopic image classification with Support Vector Machine (SVM) is presented. If a skin cancer is diagnosed early in its development, i.e., when the tumour is thin, it has a good prognosis which significantly worsens as the thickness increases. The NSST is decomposed by 4 levels with 8 directions. Finally, the SVM classifier is used for classification. The proposed system produces the classification accuracy of 96 % and its sensitivity is 93.33 % and specificity 100 %.*

Keywords *Global processing system, Non-subsampled shearlet transform, Dermoscopic images, Support vector machine*

INTRODUCTION

The growth of cutaneous cells is abnormal. It is commonly found in areas exposed to the light, but may also occur in locations that are usually not exposed to the sun. Global system classification methods in dermoscopic images are presented in [1]. It is primarily intended to organize an entire pigmented lesion into three patterns: globular, uniform and reticular. Irregular streaks are observed and examined in dermoscopic skin injury images is discussed in [2]. The appearance in a pigmented skin lesion of detected strain lines and the three-way streak classification, absent, regular, and irregular.

Four-class skin injury classification technique decomposition is described in [3]. New skin lesion classification aided computer system applicable both to melanocytic (MSL) and to nonmelanocytic MSL skin lesions. Wavelet Network (WN) approach to dermoscopic melanoma treatment is discussed in [4]. Fixed Grid Wavelet Network (FGWN) is a fixed WN that does not require gradient-type algorithms for construction; the building of the FGWN is based on a new technique of regressor selection: pursuit of D-optimal orthogonal matching and the whole system is assisted by the proposed FGWN.

Developing a dermoscopic imaging system classification for mobile devices is described in [5]. The system analyzes the skin lesions on the edge and color of the ABCD rule and classifies the lesion using a trained multi layer perceptron network using a background algorithm. Deep residual network with regularized melanoma detection fishery system is presented in [6]. A profound, convoluted neural network-based, regularized discriminant learning architecture, which extracts low dimension discriminatory features for the detection

of melanoma is suggested, as opposed to traditional computing methods that require domain expertise for segmentation and handmade feature computerization and/or selection.

Clinically important color auto-quantification in dermoscopic photographs and their application to the classification of skin lesions is described in [7]. A variety of clinically important colors are included in the measurement of malignancies in the asymmetry, boundary, color and dermoscopic law and more recent colour, design, symmetry and homogeneity. Color Constancy improvement of dermoscopic image classification is discussed in [8]. Changes in lighting and purchasing devices change image color and often reduce systems performance.

Fusion of melanoma identification structural and textural features is described in [9]. A combination of two descriptors is used with structural and textural characteristics. The structural features of the wavelet and the curvelet are taken from the various variants of the local binary model operator. Skin histopathological images automated segmentation of melanocytes is described in [10]. A new descriptor called the local double ellipse descriptor is proposed to measure the local characteristics of the candidate regions, in order to distinguish melanocytes from other keratinocytes in the epidermis area.

Automatic method of pigmented skin lesions and melanoma diagnostic decision help is described in [11]. More importantly, the decision support component includes our system which combines the results of the image classification with the background knowledge of skin type, age, gender and the body part concerned. An automated device facilitates the processing, managing and classification of dermatological photographs of pigmented skin lesions is presented in [12]. The first process requires a reproducible photographic processing method for capturing images.

An efficient method for GPS for NSST features for dermoscopic image classification with Support Vector Machine (SVM) is presented in this study. The rest of the paper is organized as follows: Section 2 describes the methods and materials used for the proposed system. Section 3 describes the results and discussion used for proposed system. The last section concludes the proposed system.

MATERIALS AND METHODOLOGY

In GPS of SLC system, the melanoma images are given to local processing system for up to n-level decomposition at first. From the sub-band coefficients of NSST, energy features are extracted. Finally, SVM classifier for all levels is used for output prediction. In GPS, the best directional features from each level are combined and the classification accuracy is improved by selecting more dominant features by a statistical approach.

GPS-Feature Extraction

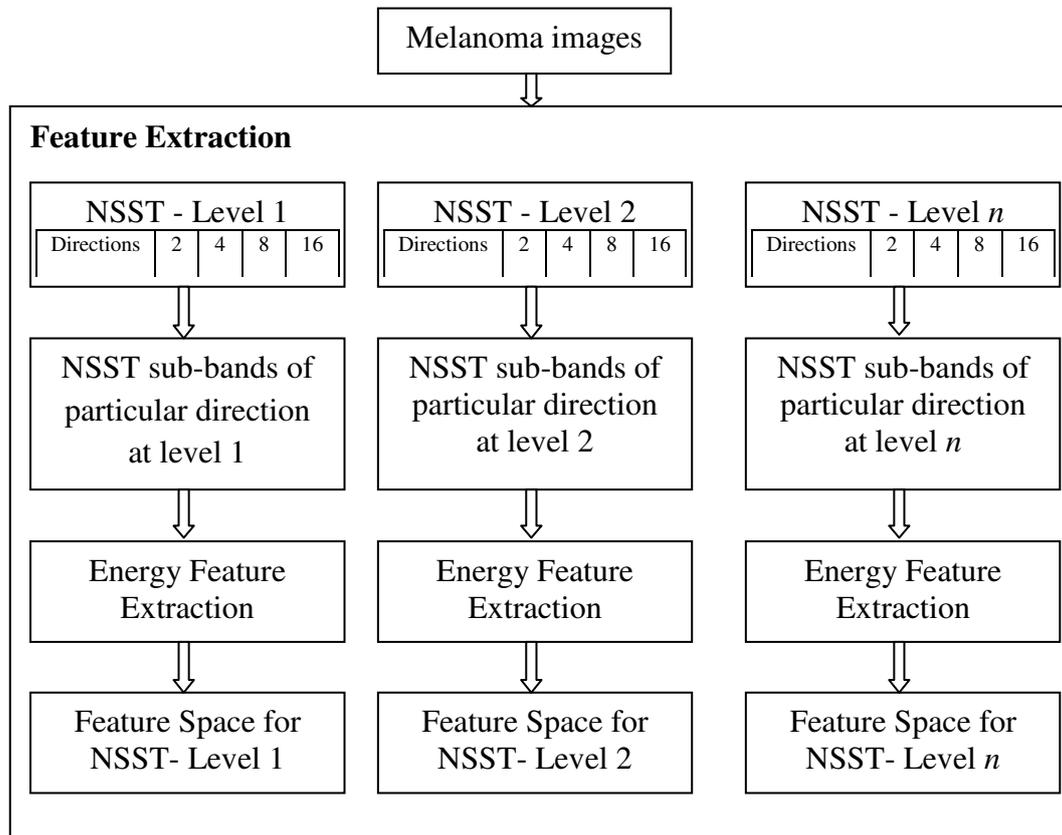


Fig.1 GPS-Feature extraction for skin cancer diagnosis

The main difference between LPS and GPS lies in the feature extraction stage. In LPS, the extracted features from the levels are used independently with all the features to SVM classifier for the classification whereas in GPS, the best features from each level are selected using a feature selection procedure in a feature selection module and fed to SVM for the classification. Figure 1 shows the process of GPS-feature extraction process.

The extracted features in the image help us to take the decisions on characteristics of an image. Hence, the dermoscopic images are subjected to the feature extraction algorithms for skin cancer diagnosis. The feature extraction step in this study is carried out by using NSST. The underlying concept of this algorithm is a multi-scale and multi-directional analysis which yields better results.

GPS-Feature Selection

Feature selection process reduces the dimensionality and retains the uniqueness of input pattern. Also, the selected features preserve the class separability very effectively. Hence, the selected features with high discriminative nature will assist the classification system effectively while the lack of discrimination reduces the accuracy of the classification system.

A t-test is a kind of inferential statistics used to determine if there is a substantial difference between the two groups' means that may be associated with certain characteristics.

The t-test is one of the methods used for statistical testing of hypotheses. To compute the t-test, three main information values are needed. A t-test tests the t-statistical values, the t-distribution values and the right to assess the statistical importance. The mean and norm discrepancy will also be significantly different to samples taken in the placebo-fed control group and from the prescribed drug. The t-test statistic value is given by,

$$t(x) = (\bar{y}_1(x) - \bar{y}_2(x)) / \sqrt{(s_1^2(x)/n_1 + s_2^2(x)/n_2)} \quad (1)$$

where $\bar{y}_1(x)$, $\bar{y}_2(x)$, $s_1^2(x)$ and $s_2^2(x)$ are the means and standard deviations of the training samples of two different classes 1 and 2 respectively. To characterize the features of dermoscopic images, energies from NSST sub-bands are extracted for only the selected NSST direction of each NSST scale. As already described in chapter 3, the mean of the magnitude of the NSST sub-bands components is computed and used as its energy.

GPS-SVM Classification

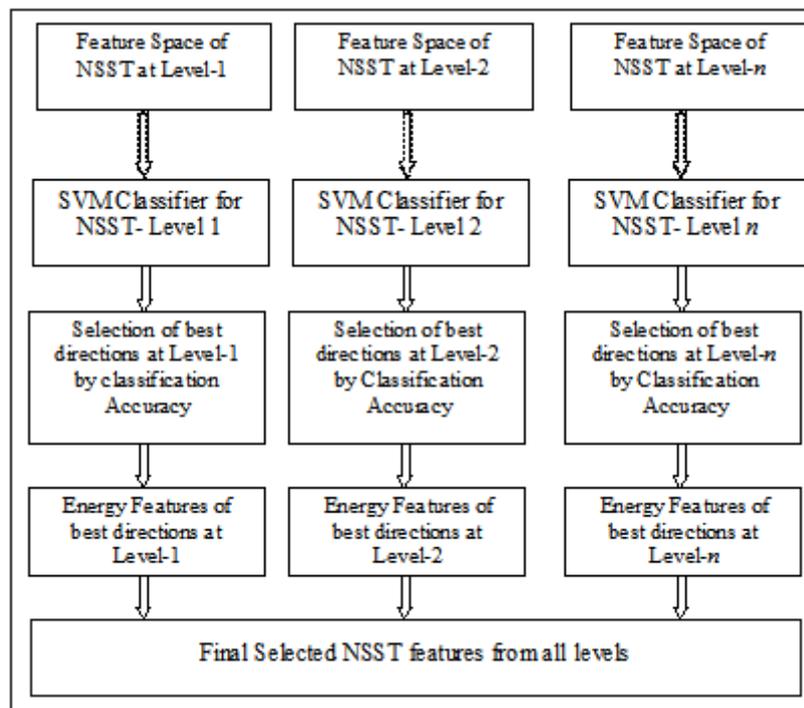


Fig. 2 GPS-Feature selection for skin cancer diagnosis

The SVM classifier is trained with the selected features and the trained SVM classifier is used to test the dermoscopic images with the help of features extracted from their NSST components. On successful classification, SVM predicts the given dermoscopic images into normal/abnormal. The goal of the SVM algorithm is to find an N-dimensional hyperplane that separates the data points. There are several potential hyperplanes to pick to differentiate the two types of data points. Maximizing the margin gap provides some reduction to maximize potential data points. Hyperplanes are decision limits that help in the classification of data points. Figure 2 shows the GPS-Feature selection for skin cancer diagnosis.

RESULTS AND DISCUSSION

The performance of proposed system is tested with dermoscopic images in PH² database [13-14]. It is freely downloadable and the resolution of each image is 768x560 pixels. It consists of 80 normal images and 120 abnormal images (40 melanoma and 80 benign images). Figure 3 shows the normal, benign and malignant dermoscopic images in the database.

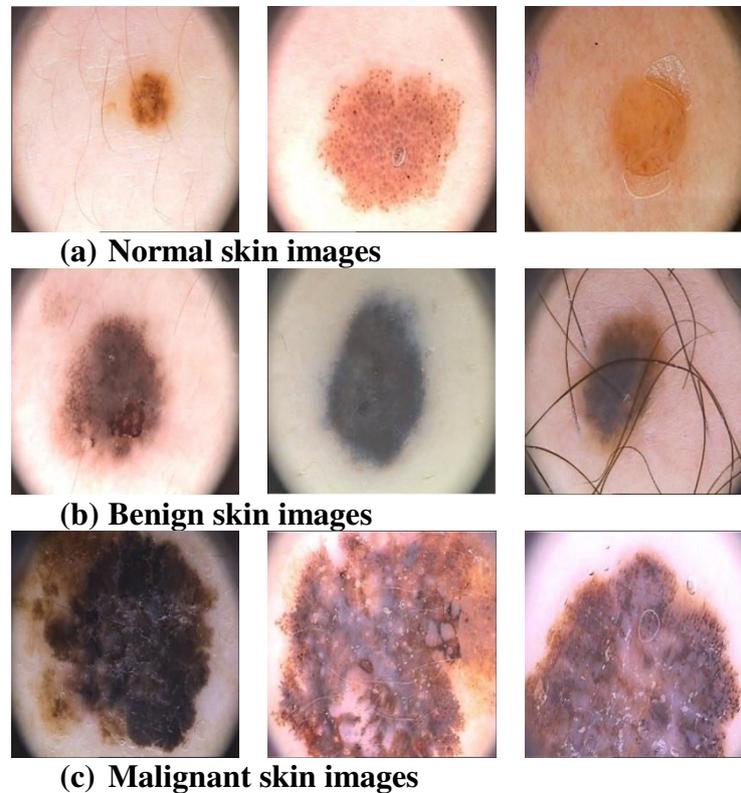


Fig. 3 Melanoma images in PH² database

In GPS, a single SVM classifier is used to classify the images based on the selected features from the best set of features from each level of decomposition. A brief summary of the performance of LPS system is shown in Table 1.

Table 1. Best Performance measures of LPS

Features	#Features	Accuracy	Sensitivity	Specificity
Level-1 (8 directions)	9	90.00	87.50	93.75
Level-2 (8 directions)	17	93.00	91.67	95.00
Level-3 (8 directions)	25	96.00	93.33	100
Level-4 (8 directions)	33	94.50	92.50	97.50

From Table 1, it is observed the total number of 8-directions features for all levels is 84. The performance measures obtained by 25% of selected features are lower than the individual analysis of 8-directions NSST-Level-3 features as only 21 features are involved whereas 25 features are involved in the individual analysis. The selection of addition features from other levels makes the performance of the system higher. The 50% of selected features provide 99.17% sensitivity and 100% specificity. Further addition of selected features reduces the system accuracy as some of them are redundant and the classifier is unable to distinguish them. The GPS with 50% features is provided higher accuracy of 99.5% than other selected features. The performance measures are computed using and are shown in Figure 4.

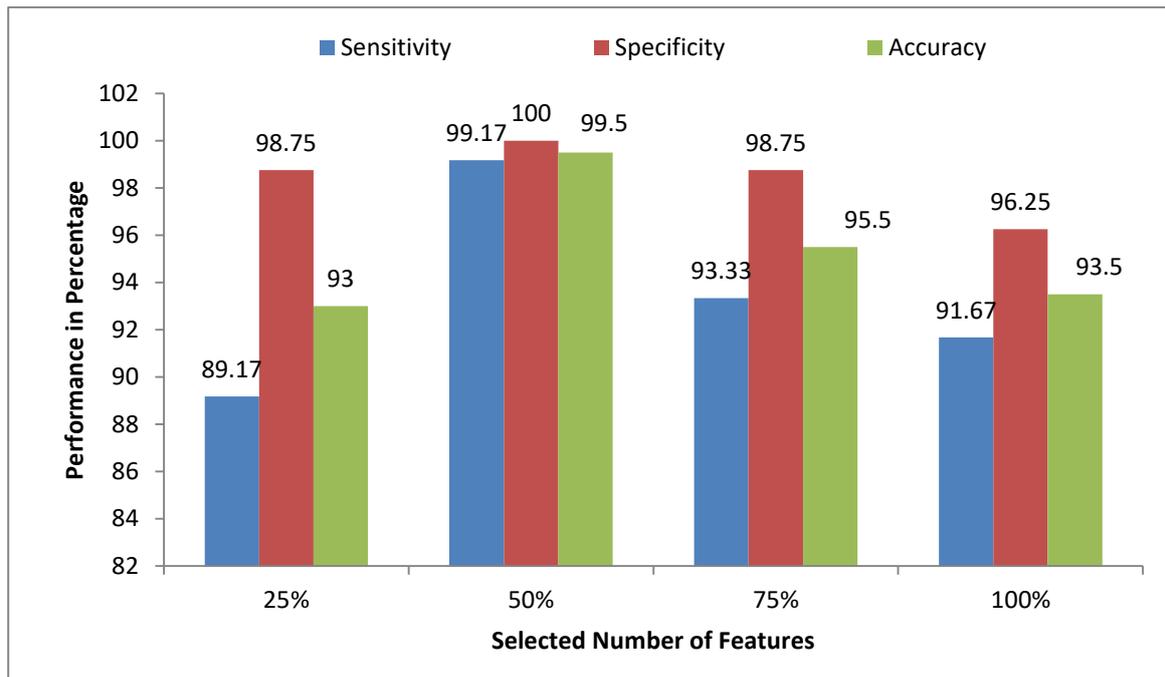


Fig. 4 Performance Measures

CONCLUSION

The efficient method for GPS based skin cancer classification using dermoscopic images is presented. The best directional features are selected based on the classification accuracy for each level. Then, the locally extracted features are fused to form a feature space. To achieve highest performance, a statistical feature selection approach is employed to select the predominant features from the feature space. These selected features are fed to SVM classifier for skin cancer diagnosis. The proposed system yields the classification accuracy of 96 % with the 25 features in 8-directions.

REFERENCES

- [1] Saez, Aurora, Carmen Serrano, and BegonaAcha. "Model-based classification methods of global patterns in dermoscopic images." *IEEE transactions on medical imaging* 33.5 (2014): 1137-1147.
- [2] Sadeghi, Maryam, et al. "Detection and analysis of irregular streaks in dermoscopic images of skin lesions." *IEEE transactions on medical imaging* 32.5 (2013): 849-861.
- [3] Shimizu, Kouhei, et al. "Four-class classification of skin lesions with task decomposition strategy." *IEEE transactions on biomedical engineering* 62.1 (2014): 274-283.
- [4] Sadri, Amir Reza, et al. "WN-based approach to melanoma diagnosis from dermoscopy images." *IET Image Processing* 11.7 (2017): 475-482.
- [5] Alencar, Francisco Eduardo Silva, Danniell Cavalcante Lopes, and Francisco Milton Mendes Neto. "Development of a system classification of images dermoscopic for mobile devices." *IEEE Latin America Transactions* 14.1 (2016): 325-330.
- [6] Sultana, Nazneen N., Bappaditya Mandal, and Niladri B. Puhon. "Deep residual network with regularised fisher framework for detection of melanoma." *IET Computer Vision* 12.8 (2018): 1096-1104.

- [7] Celebi, M. Emre, and Azaria Zornberg. "Automated quantification of clinically significant colors in dermoscopy images and its application to skin lesion classification." *IEEE systems journal* 8.3 (2014): 980-984.
- [8] Barata, Catarina, M. Emre Celebi, and Jorge S. Marques. "Improving dermoscopy image classification using color constancy." *IEEE journal of biomedical and health informatics* 19.3 (2014): 1146-1152.
- [9] Adjed, Faouzi, et al. "Fusion of structural and textural features for melanoma recognition." *IET Computer Vision* 12.2 (2017): 185-195.
- [10] Lu, Cheng, et al. "Automated segmentation of the melanocytes in skin histopathological images." *IEEE journal of biomedical and health informatics* 17.2 (2013): 284-296.
- [11] Alcón, José Fernández, et al. "Automatic imaging system with decision support for inspection of pigmented skin lesions and melanoma diagnosis." *IEEE journal of selected topics in signal processing* 3.1 (2009): 14-25.
- [12] Maglogiannis, Ilias, Sotiris Pavlopoulos, and Dimitrios Koutsouris. "An integrated computer supported acquisition, handling, and characterization system for pigmented skin lesions in dermatological images." *IEEE Transactions on Information Technology in Biomedicine* 9.1 (2005): 86-98.
- [13] Mendonça, Teresa, et al. "PH 2-A dermoscopic image database for research and benchmarking." *2013 35th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*. IEEE, 2013..
- [14] PH² Database Link: <https://www.fc.up.pt/addi/ph2%20database.html>.