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RESEARCH ARTICLE

Mobile application-based computer-aided diagnosis of skin tumours from dermal images

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ABSTRACT

Skin tumour is defined as the enormous growth of cells in the skin. The aim is to design standalone application for diagnosis of skin tumours. The dermal images of three different types obtained from the authorized PH2 database are used to analyse the defined image processing algorithm. In this algorithm, pre-processing was performed to remove hair cells. Contour-based level set is used to segment lesion from which clinical and morphological features are extracted for classification. Significant features are obtained with the feature selection technique, Random subset. Classification is performed with three classifiers. The efficiency of the classifier obtained with different trials of classification is analysed with the ANOVA test. With these results, the Multiclass Support vector machine was configured as a suitable classifier to categorize dermal images. Therefore, an application is developed for the analysis of images acquired through mobile with the help of a magnification set-up. Thus, extracted features, segmented and original images are transferred to a database for storage.

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KEYWORDS
Contour-based level set; random subset feature selection; multiclass support vector machine; standalone application

Introduction

Skin is the external layer of the body which is formed of layers, dermis and epidermis. Keratinocytes and melanocytes are the special cells which synthesize pigmented proteins called keratin and melanin, respectively.

Skin tumours occur due to the undefined growth of cells in the skin because of some metabolic reactions. Majority of the skin tumours are of benign criteria. Malignant cells are defined as skin cancer. Cancerous cells possess the nature to spread throughout the body. Skin tumours are mainly caused due to overexposure to ultraviolet radiation (UV rays) from the sun. Basal carcinoma, squamous carcinoma and melanoma are the skin cancer types common in India [1]. A common type of skin cancer, malignant melanoma, is critical and dangerous. The rate of survival of the human beings depends on the stages of cancer, if diagnosed early it is completely curable. Mole or naevus is chronic skin or mucosa lesions. Moles are generally benign but some malignant melanomas develop from the existing moles.

The signs and symptoms of melanoma include changes in the symmetry, shape and colour. Melanoma also causes itching, ulceration and bleeding. Early stages of melanoma are diagnosed using the clinical parameters such as Asymmetry Index, Border integrity, Colour variations and Diameter (ABCD) [2]. Melanoma is caused by genetic changes or DNA damage, resulting from over exposure to ultraviolet radiations from the sun. Ultraviolet radiations, UVB and UVA of wavelengths between 400 and 280 nm from the sun, are absorbed by the skin cells and cause DNA damage leading to abnormal growth of the melanocytic cells. The common diagnostic technique used to diagnose the symptoms of skin tumours are Dermoscopy and Biopsy. The dermoscopy method is mainly for the visual examination of the lesion and outgrowths in the skin cells. Another technique for diagnosis is skin biopsy in which a sample of the lesion from the skin is removed and transferred to the pathologist for analysis [3].

Skin tumours are becoming predominant among tropical countries which maybe cancerous. Statistical and survey studies have been carried throughout India particularly in certain hospitals with the skin cancer patients [1,4]. This study reveals that skin cancer is becoming predominant and early diagnosis of skin cancer is very much necessary. Diagnosis and treatment are required for these skin cancers for immediate and easy recovery. The main objective is to develop a computer-aided standalone application system for early diagnosis of skin tumours or disorders. In these three types of database dermal images are categorized and classified using the image processing algorithm. Later mobile acquired images using a magnification lens are analysed using the same defined algorithm in the standalone application designed for the Windows platform. Early detection and diagnosis are very much required in such cases. Many types of research have been carried out related to the diagnosis application.

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Abuzaghleh et al. [5] explain that database images of melanoma can be analysed and classified into different types of pigmented skin diseases [5]. The real-time alert system developed for the early detection of different skin burns. ABCD are the features described for the diagnosis of melanoma skin cancer. Database images are analysed and used for segmentation, feature extraction by ABCD features and classification using support vector machines (SVM). The automatic image analysis model developed for acquisition, lesion segmentation, feature extraction and classification of skin images has great accuracy.

Philips et al. [6] describe the design of a mobile application for melanoma detection in android smartphones [6]. Applications are developed with the Android Developer Tools and also processed in MATLAB to classify the images as benign or malignant using the SVM model. The efficiency of the SVM classifier model is determined with the database images.

Karagyris et al. [7] describe that using machine language an automatic real-time acquisition module can be developed and used for early detection of the skin cancer images [7]. These Android applications are more or less similar to the proposed methodology. But the application created in this case is related to the Windows system (standalone application).

Application in real time is designed in iPhone for the early diagnosis of skin cancer. A magnifying lens of various magnifications is used to determine the real-time images. Two class classifiers are used to determine and diagnose the different types of skin cancer. With the review of the literature and study performed about the analysis of dermal images, the aim is to develop a standalone application for the classification of skin tumours.

Proposed methodology

This paper proposes a computer-aided standalone application for the diagnosis and analysis of skin tumours in the human body. The proposed system defines the development of a standalone application for diagnosis. Dermal images from a standardized database as the PH2 dermoscopic database is used to analyse and study the defined Image Processing Algorithm. Three different categories of images (benign tumours, normal moles and malignant melanoma) are selected and processed. The process of hair removal is carried out to define a clear lesion from the skin images through the dilation process. Contour-based level set segmentation is used for lesion separation and feature extraction to classify the images into three different categories. Feature selection is used to configure the dominant and significant features. The dominant features are considered for classification with three different types of classifiers such as Backpropagation network, Pattern recognition network and SVM. Performance parameters of the classifiers are obtained to determine the accurate

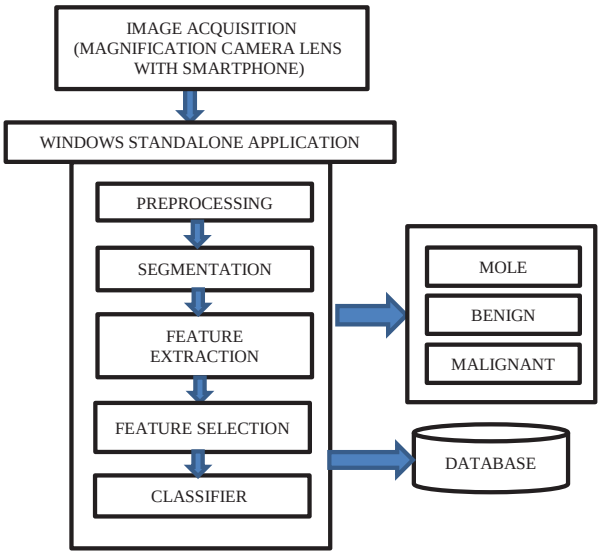


Figure 1. Proposed methodology for diagnosis of dermal images.

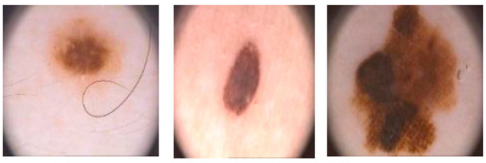
classifier for these database dermal images. With these performance results, the Multiclass Support Vector Machine is defined as the best classifier. An algorithm is developed as a standalone application with the SVM classifier to analyse the dermal images captured using mobile with the magnification lens of power 20×. The application results along with the image are transferred to the database for storage. Therefore, the proposed methodology for classification and identification of skin tumours is shown in Figure 1.

Dermoscopic images are obtained from the database of skin cancer for the diagnosis system. The PH2 database is an authorized and standardized database accepted by many dermatologists all over the world [8]. Dermal images from these databases are used for the analysis of the defined algorithm for diagnosis. Images in the databases are obtained with the help of the dermoscope system with a magnification power of 20× and resolution of 768,560 pixels. Databases possess more than 5000 images of skin tumours which include abnormal naevi, melanomas, common naevi and benign tumours [5]. Out of which 1500 images are collected for three different types of skin tumours such as 500 from atypical naevus (benign tumours), 500 from malignant melanoma and 500 from common naevus (moles). Images in this database are not processed and normalized, it consists of all the features that the image possesses during a real-time acquisition. Many types of research used these databases for the detailed study and analysis of the skin cancer images [2,5,9]. The database images are shown in Figure 2.

Pre-processing

Dilation

A pre-processing technique such as the dilation process is performed for the removal of hair cells



(a) (b) (c)

Figure 2. Sample database images: (a) normal mole, (b) benign tumour and (c) malignant melanoma.

from the skin lesion images. Hair cells obstruct the clear vision of the lesion in the dermal image. In this process, hair cells are removed by a morphological operation called greyscale dilation in which the structural function is defined over the image. This enables better segmentation of lesion and extraction of features from the dermal images [10,11]. Greyscale dilation is done with the help of the dilation operation as shown in the Equation (1) with $f(x)$ as the image function and $b(x)$ as the structuring function in Euclidean space (E)

$$(f \oplus b)(x) = \sup[f(y) + b(x-y)] \text{ for all } y \in E \quad (1)$$

where x and y are pixel coordinates of an image.

Contrast stretching

Database images possess slight intensity level variations when compared with the mobile acquired images. Intensity variations are adjusted using contrast stretching. Contrast stretching is an enhancement technique in image processing which is mainly used to adjust the intensity values in a desired range of values. Contrast stretching is explained in Equation (2)

$$A = (r-c)\left(\frac{b-a}{d-c}\right) + a \quad (2)$$

where a, b, c and d are upper and lower limits of grey levels considered for the process of contrast stretching, respectively, and r defines the total number of greylevels considered.

Segmentation

Segmentation is mainly to separate the lesion in the skin from the background in which the contour-based level set segmentation method is defined for the separation of the lesion from the skin surface. In this, a level set function is determined for the curvature of the lesions in the greyscale dilated images, which defines the lesion curvature in a binary image. Superimposition burning of the binary image over the original image derives the lesion without any background [5]. The contour level set method is defined in Equation (3) with Ψ as a function for the level set, v as speed and t time

$$\frac{\partial \Psi}{\partial t} = \nu|\nabla\Psi| \quad (3)$$

Feature extraction

In the feature extraction process, totally 15 features are derived. They are morphological features (two parameters), diagnostic clinical features (ABCD) of seven parameters, statistical features and GLCM (Grey Level Co-occurrence Matrix) features (five parameters). Clinical features described by the dermatologists as ABCD features help in the identification and determination of the different types of skin tumours. These features involve ABCD that exactly and specifically explain the nature of the lesions or tumours [11].

Asymmetry Index

The Asymmetry Index (AI) defines that the shape of one half that does not match the rest half. The severity of the skin cancer depends on the asymmetry degree of a skin lesion. So, asymmetry around both minor and major axes needs to be calculated. AI is calculated as shown in Equation (4) with ΔAmax and ΔAmin corresponding to the non-overlapping areas along the major and minor axis, respectively. A is the total area of the lesion

$$\text{AI} = \frac{\Delta A\text{max} + \Delta A\text{min}}{2*A} \quad (4)$$

Border irregularity

Irregularity of the lesion boundaries is termed as border irregularity. Malignant lesions are more irregular than benign. Two parameters are used to define the border irregularity of the lesions. Compactness Index measures roundness in a two-dimensional object. The Index is sensitive to the noise defined around the boundary of the lesion. It is defined in Equation (5) with P as the perimeter of the lesion and A as an area of the lesion

$$\text{CI} = \frac{P^2}{4\pi A} \quad (5)$$

The Circularity Index measures the circular nature of the lesion or defines the outline based on the curvature of the lesion which is explained by Equation (6)

$$\text{Circularity index} = \frac{4\pi A}{P^2} \quad (6)$$

Colour variation

The colour variance parameter analyses the colour distribution of the lesion. It checks variation of colour from the centre to its boundary. Colour distribution throughout the lesion in the skin is defined with the mean and standard deviation (SD) which are the statistical parameters.

Diameter

Diameter is mainly to determine the type of lesion which is defined by the major axis and minor axis of the lesion structure. Mostly malignant lesions have more diameter than benign or naevus samples (larger than six millimetres or about a quarter inch for malignant melanoma).

GLCM is used to define certain features corresponding to the second order statistical probability $P(i, j)$. Contrast, correlation, entropy, energy and homogeneity are GLCM features described below in Equations (7)–(11) with i and j being grey levels, n as the number of grey levels and x, y as pixel coordinates.

Contrast is a measure of local contrast or intensity variations between the grey levels i and j

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \left\{ G \sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j) \right\}, \quad |i - j| = n \tag{7}$$

The measure of linear dependence among the pixels at the relative position specified to each other is defined as correlation.

$$\text{Correlation} = \sum_{i=1}^{G} \sum_{j=1}^{G} (\{i \times j\} P(i,j) - \{\mu x \times \mu y\}) / \sigma x \times \sigma y \tag{8}$$

Entropy is a statistical form of randomness to characterize the texture of the image.

$$\text{Entropy} = -\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \times \log(P(i,j)) \tag{9}$$

Maximum or periodic uniform values in the grey level distribution describe the maximum energy of texture.

$$\text{Energy} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (P(i,j))^2 \tag{10}$$

Homogeneity among the grey level pixels of the image is described in Equation (11).

$$\text{Homogeneity} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left({}^{1}\!/_{1 + (i-j)^2} \right) [P(i,j)] \tag{11}$$

These 15 features undergo the feature selection process to obtain significant and dominant features for effective classification.

Feature selection

The feature selection technique is used mainly to obtain dominant features which completely define the characteristics of the lesion in the image. Dominant features for the classification process are determined using the Random Subset Feature Selection (RSFS) technique. RSFS is a feature selection method in which the random subset of features is used to determine the significant features [2]. These features are obtained by repetitively classifying the data with a k-NN classifier while using randomly chosen subsets of all possible features and adjusting the relevance value of each feature according to the classification performance of the subset. Thus, seven features such as AI, Colour Variation, Compact Index, Mean, Energy, Contrast and Entropy with the 99% of probability are described as the dominant features. With these features, the classification of images is carried out.

Classification

Three types of classifiers such as backpropagation network, pattern recognition network and SVM are used to differentiate the different categories of images. The efficiency of the classifiers is studied and analysed with the help of the performance parameters of classification.

The backpropagation neural network (BPN) is useful for complex pattern recognition and mapping functions. For each output unit, the backward flow of error signals are computed with the input units. The pattern recognition neural network mainly focuses on the recognition of patterns and data regularity [12]. SVM are supervised machine learning algorithms or models. SVM is the representation of points that map to form separate divisions and a clear boundary is defined called as the decision boundary [13]. In the multiclass support vector machine different classes are optimized with the kernels.

Dominant features are considered for classification using three different classifiers. The confusion matrix is obtained for each classifier in order to learn their performance which is defined using certain parameters such as accuracy, precision, specificity and sensitivity. These parameters are calculated based on the true positive (TP), false positive (FP), true negative (TN) and false negative (FN) values obtained from the confusion matrix [14].

Accuracy is defined as the observational error that describes the trueness of the classification function. Precision defines the statistical variability of random errors and is related to the reproducibility and repeatability state of classification. Accuracy and precision are defined in terms of TP, TN, FN and FP and are shown in Equations (12) and (13).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{P} + \text{N}}, \quad \text{P} = \text{TP} + \text{FN}, \text{N} = \text{FP} + \text{TN} \tag{12}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{13}$$

Sensitivity and specificity are classification performance tests which involve statistical measures. Sensitivity

and specificity measure the positive and negative proportions that are correctly defined, respectively. They are described in Equations (14) and (15).

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{14}$$

$$\text{Specificity} = \frac{\text{FP}}{(\text{FP} + \text{TP})} \tag{15}$$

Performance parameters are used to define the effective and efficient classification nature of the three different classifiers. The one-way ANOVA test is performed for the performance parameters of the classification process. In this process, each classifier is accessed for 10 trials and performance parameters are determined for each trial. With the overall values of performance parameters of three classifiers for all trials, the *P*-value and honestly significant difference (HSD) is obtained. The *P*-value describes the significance of variations between the two samples. HSD is defined using the Tukey test which is a multiple statistical comparison procedure. With the results obtained, the SVM classifier is defined as the best classifier for classification of skin tumours from dermal images.

Standalone application

A standalone application is developed and designed with image processing techniques and SVM classifier for the classification of dermal images acquired using mobile phone through a 20× magnification lens. The magnification lens of 20× power is defined in Figure 3.

The dermal images acquired through smartphones with the help of a magnification lens of power 20×. 20× magnification lens is mainly used to resemble the nature of the database of images which is considered for the designing and development of the algorithm. Database and mobile acquired images of skin tumours possess slight variations in the intensity level, but the acquisition set-up for both the types of images is similar. The intensity levels of acquired images are adjusted using the contrast stretching process before

Figure 3. Magnification lens of power 20×.

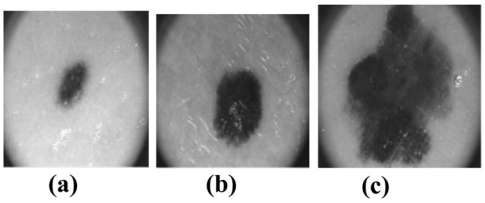


Figure 4. Original images: (a) normal mole, (b) benign tumour and (c) malignant melanoma.

the dilation in pre-processing. The algorithm used for database images is used to analyse the mobile acquired images. Mobile acquired images are transmitted to the windows platform or system through Bluetooth. Graphical User Interface (GUI) is designed for the algorithm. With the help of GUI, a standalone application for windows platform is developed. The standalone application performs the image processing techniques for the analysis and diagnosis of the skin tumours from the dermal images transferred through Bluetooth from the smartphone. The extracted features and the processed images from the standalone application are transferred to the database through the local server for storage purpose. A local server with the image database is developed for the storage of the processed mobile acquired images. Thus, the mobile acquired images are processed using the standalone application and stored in the database for future usage.

Results and discussions

In the proposed method, the PH2 database dermoscopic images are used to analyse the defined image processing algorithm. The dermoscopic images of three categories benign tumours, common moles and malignant melanoma are processed and lesions are segmented separately. In which the RGB images are converted into greyscale images as shown in Figure 4.

The greyscale dilation process is carried out to remove the hair cells. In this morphological operation, the disc structuring element is used as a function over the image to obtain a pre-processed image. Disc size is configured to be two radius because this is the exact size which removes the hair cells in the dermal images without any change in the pixels of the image. Even though this radius shows slight pixel variations it has an effective range to remove the hair cells

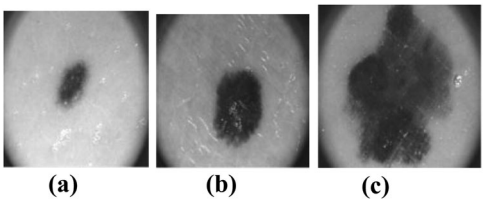


Figure 5. Dilation processed images: (a) normal mole, (b) benign tumour and (c) malignant melanoma.

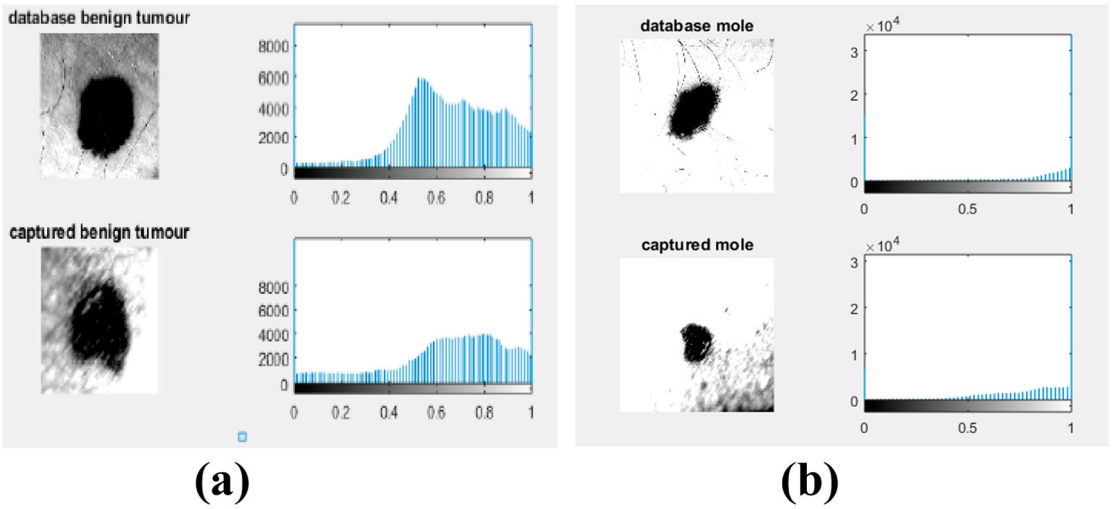


Figure 6. Contrast stretched mobile acquired images with histogram equalization (a) benign tumour and (b) normal mole.

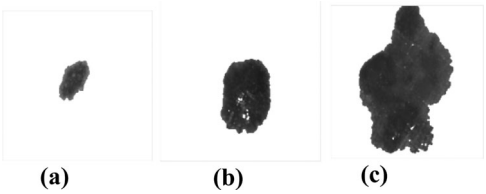


Figure 7. Superimposed segmented images: (a) normal mole, (b) benign tumour and (c) malignant melanoma.

and retain the pixels. Dilation processed database images are shown in Figure 5.

For mobile acquired images, the intensity levels are adjusted through Contrast Stretching, to make it compatible for the defined algorithm. Histogram equalization is obtained for both normal database images and mobile acquired images after the contrast stretching process which is defined in Figure 6.

The contour-based level set method is used in the segmentation of the lesion from the images. A level set function defined for the curvature and a curvature image is obtained as a mask. This mask is used to obtain the lesion separately by superimposition of the original image. Superimposed segmented images are defined in Figure 7.

Feature extraction is carried out in the segmented lesion image. Fifteen features are extracted including the diagnostic clinical features, morphological and statistical features. ABCD are the clinical features obtained from the lesion segmented from the background.

The features undergo the RSFC process from which efficient and dominant features are derived for the classification process. In this process from the random subset of 15 features, 7 significant features are determined with 99% of probability using the k-NN algorithm. Significant nature of features is further analysed with the statistical values such as mean and SD. Based on the statistical values and the feature selection process, seven features are termed as dominant features. These statistical values of the seven significant features are obtained as a result of the RSFC process and are described in Table 1.

Three different classifiers are used to analyse and classify the skin tumours from the dermal images with the dominant features obtained. The confusion matrix is defined with TN, TP, FN and FP for all the three categories of dermal images. Classifier 1 is the backpropagation network in which both training and testing occur. Classifier 2 is the pattern recognition mainly defined to recognize complex patterns and mappings. Classifier 3 is the support vector machine (SVM) in which a margin of separation the so-called decision boundary separates the positive and negative classes of the input samples with predefined values.

Table 1. RSFS-based selected features (seven features).

		Normal		Benign		Malignant	
Classes		Mean	SD	Mean	SD	Mean	SD
Seven significant features	Colour						
	Mean	0.444	0.020	0.431	0.054	0.426	0.066
	Mean	122.4	19.75	106.7	20.20	84.21	14.49
	Energy	0.727	0.159	0.672	0.143	0.588	0.145
	Contrast	0.081	0.057	0.108	0.043	0.183	0.086
	Entropy	1.505	0.878	1.830	0.831	2.297	0.917
	Compact Index	1.790	0.608	2.032	0.788	2.705	1.268
	AI	47.16	2.448	46.56	2.934	40.48	8.785

Table 2. Efficiency results with increasing hidden units or kernels.

Classifiers	Number of hidden units or kernels	Performance parameters			
		Accuracy	Precision	Specificity	Sensitivity
BPN	10	93.8	0.938	0.969	0.9399
	20	94.33	0.9433	0.9717	0.9454
	30	94.6	0.946	0.973	0.9482
	40	94.4	0.944	0.9720	0.9465
PNN	10	94.5333	0.9453	0.9728	0.9451
	20	96.2667	0.9627	0.9814	0.9625
	30	96.5333	0.9753	0.9877	0.9756
	40	96.7667	0.9767	0.9883	0.9767
SVM	10	98.2	0.982	0.9910	0.9823
	20	98.4667	0.9847	0.9923	0.9851
	30	98.6667	0.9867	0.9933	0.9867
	40	98.7333	0.9873	0.9937	0.9875

Table 3. Percentage of classification performance parameters.

	Percentage of performance parameters			
	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
BPN	94.45	0.94	0.97	0.95
PNN	96.30	0.97	0.99	0.96
SVM	98.53	0.99	0.99	0.99

The Radial Basis Function kernel is used in multiclass SVM for classification.

Performance of classification of each classifier is determined using certain parameters such as Accuracy, Precision, Sensitivity and Specificity. These parameters are derived with the confusion matrix of each classifier that categorizes the three different classes of dermal images. With the increase in the hidden units or kernels, the classification performance increases which is shown in Table 2. The hidden units or kernels are increased from 10, 20, 30 and 40 which show changes in the efficiency of the classification process.

Percentage of each parameter describes the accurate and efficient classifier for dermal image diagnosis. Percentage of classification performance is described in Table 3.

In this process, three different classifiers are compared with accuracy and efficiency of classifier 1 (BPN) is 94%, classifier 2 (PNN) is 96% and classifier 3 (SVM) is 98%. Thus, the classifier 3 (SVM) which is based on machine learning is defined to be more efficient compared to other classifiers.

The one-way ANOVA test is performed for the classification performance parameters which are obtained for each trial of classification by all the three classifiers. Maximum of 10 trials are carried with the 3 classifiers for which accuracy, precision, specificity and sensitivity are calculated. With these values obtained for the 10 trials, the ANOVA test is performed. Based on the classification performance and ANOVA test results, Classifier 3 (Multiclass SVM) is defined as the best classifier for identification and classification of skin tumours. The one-way ANOVA test reveals that when the P-value < 0.01 or <0.05 then it is 99 or 95% of confidence level, respectively, for the performance parameter measures for 10 trials. Consolidated results of one-way ANOVA test are described in Table 4.

Tukey's test defines the HSD between the group means and comparison of group variations. HSD is also used to enumerate the efficiency of classification. The results of Tukey's test are shown in Table 5. Thus, one-way ANOVA and Tukey's test explain the best conclusion for the efficient classification process to be the support vector machine.

Table 4. Consolidated results of one-way ANOVA test.

Parameters	BPN	PNN	SVM	P
Accuracy	93.8	95.9333	98.2	
	94.3333	96.2667	98.4667	
	94.6	97.5333	98.6667	
	94.4	96.6667	98.7333	
	94.6133	96.6	98.1333	<.0001
	94.6	97.2	98.4667	
	94.8	96.4667	98.6667	
	94.4	96.6667	98.7333	
	94.3333	97.6	98.5333	
	94.6	97.0667	98.7333	
Mean stats	94.448	96.30001	98.53333	
Precision	0.9399	0.9451	0.9823	
	0.9454	0.9625	0.9851	
	0.9482	0.9756	0.9867	
	0.9465	0.9767	0.9875	
	0.9454	0.9765	0.9814	<.0001
	0.9482	0.9727	0.9851	
	0.9495	0.9849	0.9867	
	0.9465	0.9767	0.9875	
	0.9454	0.9765	0.9854	
	0.9482	0.9806	0.9875	
Mean stats	0.9463	0.97278	0.98552	
Specificity	0.969	0.9728	0.991	
	0.9717	0.9814	0.9923	
	0.973	0.9877	0.9933	
	0.972	0.9883	0.9937	
	0.9717	0.988	0.9907	<.0001
	0.973	0.986	0.9923	
	0.974	0.9924	0.9933	
	0.972	0.9883	0.9937	
	0.9717	0.988	0.9927	
	0.973	0.9903	0.9937	
Mean stats	0.9721	0.98632	0.9927	
Sensitivity	0.938	0.9453	0.982	
	0.9433	0.9627	0.9847	
	0.946	0.9753	0.9867	
	0.944	0.9767	0.9873	
	0.9433	0.976	0.9813	<.0001
	0.946	0.972	0.9847	
	0.948	0.9847	0.9867	
	0.944	0.9767	0.9873	
	0.9433	0.976	0.9853	
	0.946	0.9807	0.9873	
Mean stats	0.9442	0.97261	0.9823	

Table 5. Consolidated results of Tukey's test.

Parameters	BPN	PNN	SVM	Tukey's test
Accuracy	93.8	95.9333	98.2	
	94.3333	96.2667	98.4667	
	94.6	97.5333	98.6667	HSD[.05] = 0.01
	94.4	96.6667	98.7333	HSD[.01] = 0.01
	94.6133	96.6	98.1333	M1 vs. M2 P <0 .01
	94.6	97.2	98.4667	M1 vs. M3 P < 0.01
	94.8	96.4667	98.6667	M2 vs. M3 P < 0.01
	94.4	96.6667	98.7333	
	94.3333	97.6	98.5333	
	94.6	97.0667	98.7333	
Mean stats	94.448	96.30001	98.53333	
Precision	0.9399	0.9451	0.9823	
	0.9454	0.9625	0.9851	
	0.9482	0.9756	0.9867	
	0.9465	0.9767	0.9875	HSD[.05] = 0
	0.9454	0.9765	0.9814	HSD[.01] = 0.01
	0.9482	0.9727	0.9851	M1 vs. M2 P <0 .01
	0.9495	0.9849	0.9867	M1 vs. M3 P <0 .01
	0.9465	0.9767	0.9875	M2 vs. M3 P <0 .05
	0.9454	0.9765	0.9854	
	0.9482	0.9806	0.9875	
Mean stats	0.9463	0.97278	0.98552	
Specificity	0.969	0.9728	0.991	
	0.9717	0.9814	0.9923	
	0.973	0.9877	0.9933	HSD[.05] = 0.01
	0.972	0.9883	0.9937	HSD[.01] = 0.01
	0.9717	0.988	0.9907	M1 vs. M2 P < 0.01
	0.973	0.986	0.9923	M1 vs. M3 P < 0.01
	0.974	0.9924	0.9933	M2 vs. M3 P < 0.01
	0.972	0.9883	0.9937	
	0.9717	0.988	0.9927	
	0.973	0.9903	0.9937	
Mean stats	0.9721	0.98632	0.9927	
Sensitivity	0.938	0.9453	0.982	
	0.9433	0.9627	0.9847	
	0.946	0.9753	0.9867	HSD[.05] = 0.49
	0.944	0.9767	0.9873	HSD[.01] = 0.62
	0.9433	0.976	0.9813	M1 vs. M2 P < 0.01
	0.946	0.972	0.9847	M1 vs. M3 P< 0.01
	0.948	0.9847	0.9867	M2 vs. M3 P <0 .01
	0.944	0.9767	0.9873	
	0.9433	0.976	0.9853	
	0.946	0.9807	0.9873	
Mean stats	0.9442	0.97261	0.9823	

With the help of the SVM classifier, the mobile acquired dermal images are processed in a standalone application. Mobile acquired images are obtained by using the smartphone camera attached with a magnification lens of power 20×. In Figure 8, the magnification set-up for mobile acquired images is shown.

Figure 8. Magnification setup for mobile acquired images.

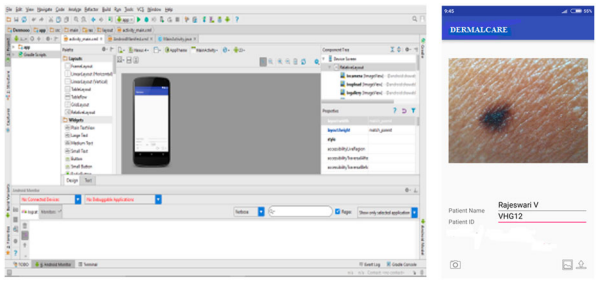


Figure 9. Android camera application for acquistion of dermal images.

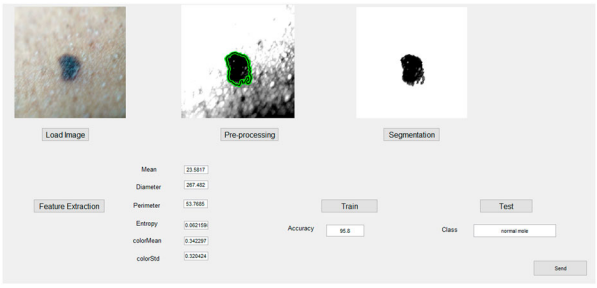


Figure 10. GUI-based standalone application for Windows platform.

Mobile application is developed for the acquisition of dermal images with the magnification lens of power 20×. The mobile acquired images are captured through the camera application developed and transferred to the windows system through Bluetooth. The Android Camera Application for acquisition of dermal images is shown in Figure 9.

GUI for the defined image processing algorithm is designed with the help of the multiclass SVM classifier for classification training and testing. The GUI designed is used to develop the standalone application for windows platform. This standalone application performs all image processing techniques for the classification of mobile acquired images into different categories. The mobile acquired dermal images are processed and classified with the standalone application for the diagnosis of skin tumours. The processed image and extracted features are transmitted to the database for storage. GUI-based standalone application for windows platform is shown in Figure 10.

From the standalone application, the processed image and extracted features are transmitted to the

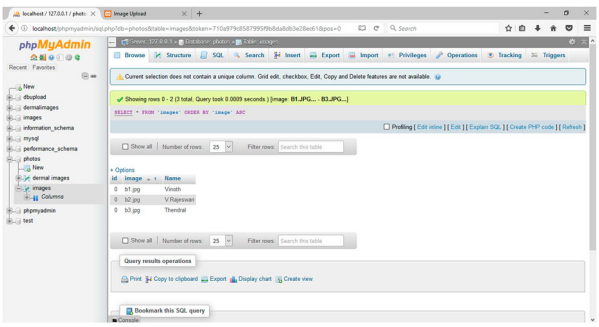


Figure 11. Webpage with the image database for storage.

database through local server connection. A local server with the webpage is used to develop the image database for storage. Database possesses the details of the processed image and extracted features from the dermal images. Database along with the image details is shown in Figure 11.

Thus, dermal images are acquired through the mobile application with the magnification lens attached to the camera of the mobile. From the mobile application, the images are transferred to the windows platform through Bluetooth. The standalone application performs the image processing and classification of the transferred mobile acquired images in the windows platform. After processing, the images and extracted features are transmitted to the database for storage and future usage purpose. Skin cancer classification-based applications are available which define the entire processing for identification and features study is enumerated. ABCD features are analysed mainly in the previous studies. In this study, the platform is made comfortable for windows and android is used for acquiring images. Storage of the resultant image and extracted features in the database is an additional specialty of the methodology in this paper.

Conclusion and future work

The incidence of skin cancer is increasing among individuals. Early detection of skin cancer is necessary to treat patients effectively. Since surgical excision is the only lifesaving treatment method for skin cancers. Therefore, early detection and diagnosis are necessary. In this methodology, database images of three different categories such as common mole, benign tumour and malignant melanoma undergo image analysis processes such as hair detection and removal, segmentation of the lesion, feature extraction, feature selection and classification to determine the nature of the algorithm described. Classification is carried out with three different classifiers such as the backpropagation network, pattern recognition network and support vector machine. Efficiency and performance of the classification process of each classifier are determined using the performance parameters from the confusion matrix. The one-way ANOVA test is performed to define the significant classification process. The multiclass support vector machine of 98% is described to be efficient for the classification of dermal images. From the results, a standalone application for diagnosis is developed for the classification of skin tumours. The mobile application is designed for acquisition of dermal images through the magnification lens of power 20×. From the android application, the images are transferred through Bluetooth to the Windows platform in which the images are processed with the help of the standalone application. The processed images and extracted features are sent to the database for storage through local server connection.

Future work focuses on the development of a real-time android application which can help the dermatologists more effectively in early detection and diagnosis with different levels of magnification. Further development in the work includes the formation of an Indian database for skin tumours and extending the diagnosis for real-time skin tumour images of different categories.

Disclosure statement

No potential conflict of interest was reported by the authors.

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