Computer Aided Diagnosis of Skin Tumours from Dermal Images

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Abstract. Skin tumour is uncontrolled growth of skin cells which may be cancerous. The aim is to develop computer aided diagnosis for skin tumours. The dermal images of three types such as benign tumour, malignant melanoma and normal moles obtained from the authorised PH2 database. Pre-processing performed to remove hair cells. Contour based level set technique for segmentation of the lesion from which clinical and morphological features are extracted. The significant features are obtained using Random Subset Feature Selection technique. Classification is performed using three classifiers such as back propagation, pattern recognition and support vector machine. Classifier Efficiency of three classifiers is determined to be 94, 96 and 98% respectively with the Classifier performance parameters. One way ANOVA test is performed to analyse the efficiency of the three classifiers. With these results, Support vector machine is configured as accurate classifier for classification.

Keywords: Contour based level set · Random subset feature selection

1 Introduction

Skin is the outermost layer of the human body. Skin is formed of two layers epidermis and dermis. Melanin and keratin are the two pigment proteins produced by the special types of cells called melanocytes and keratinocytes respectively. Damage to any layer of the skin occurs in different ways and they are of various types. Skin tumours are developed due to the uncontrolled growth of the skin cells due to some metabolic changes. Majority of the skin tumours are benign. Malignancy of skin tumours defined as Skin cancers. Cancerous cells have the ability to spread all over the body. Skin tumours are mainly caused due to overexposure of ultraviolet radiation from the sun. Most common types of skin cancer are basal carcinoma, squamous carcinoma and melanoma. Melanoma is a common type of skin cancer that is dangerous and critical even leads to death of the human beings. The survival rate of the patients depends on the stages of cancer if diagnosed early it is completely curable. Mole or nevus is chronic skin or mucosa lesions. Moles are benign but 25% of malignant melanomas arise from the existing nevi [1].

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The signs and symptoms of melanoma include changes in the shape and colour of the moles or nodular melanoma. Melanoma also causes itching, ulcerate and bleeding. Early stages of melanoma are defined using Asymmetry, Borders, Colour variations and Diameter [2]. Melanoma is caused by DNA damage resulting from exposure to ultraviolet radiations from the sun. Genetics also plays an important role in the melanoma formation. Ultraviolet UVB and UVA radiations of wavelengths between 400 and 280 nm from the sun is absorbed by the skin cells and causes DNA damage leading to uncontrolled growth of the melanocytes. Common diagnostic technique is to analyse the signs and symptoms of skin tumours using Dermoscopy and Biopsy. Dermoscopy method is mainly for the examination of the lesion and outgrowths. Other technique used for diagnosis is skin biopsy in which a skin lesion is removed and sent to the pathologist for study.

Survey study has been carried out in India particularly in certain hospitals with the skin cancer patients [3, 4]. This study reveals the truth that skin cancer is becoming predominant and early diagnosis of this is very much necessary. Basal cell carcinoma, squamous carcinoma and malignant melanoma are common types of skin cancer seen in India. Melanoma rate increased in India [4]. Diagnosis and treatment is required for these skin cancers immediately for easy recovery. The purpose is to develop a computer aided diagnostic system for early detection and diagnosis of skin tumours. In this three different types of dermal images are categorised and classified. Malignant melanoma is very dangerous and critical form of skin cancer. Early diagnosis and detection is very much required in such cases. Many researches have been carried out related to the computer aided diagnosis [5].

Abuzaghleh et al. [6] explains that database images of melanoma can be analysed and classified into different types of pigmented skin diseases [2]. Real time alert system developed for the diagnosis and early detection of skin burns. Asymmetry, Border, Colour and Diameter (ABCD) are the features described for the diagnosis of melanoma skin cancer. Database images are used for segmentation, feature extraction by ABCD features and classification using SVM. Automatic image analysis model developed for acquisition, lesion segmentation, feature extraction and classification of skin images with great accuracy.

Fosu and Jouny [7] describes the development of a mobile application for melanoma detection in android smart phones. Applications are developed with the Android Developer Tools and also processed in MATLAB to classify the images as benign or malignant using support vector machines (SVM) model. The classification in MATLAB is based on the colour and symmetry analysis of the melanoma images. The efficiency of the SVM classifier model is determined with these database images. Karargyris et al. [8] describes that using machine language an automatic real time acquisition module can be developed and used for early detection of the skin cancer images. Application in real time is developed in iPhone for the early detection of skin cancer in general. Two class classifiers are used to determine and monitor 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 computer diagnostic system for the skin tumours. Processing of the dermal images is defined to obtain an accurate and efficient system for diagnosis.

2 Proposed Methodology

This paper proposes a computer aided diagnosis technique for skin tumours in human body. Skin tumours are formed mainly due to over exposure of Ultraviolet Radiation that may also lead to cancer [3]. The proposed system defines that for development of the diagnosis system, dermal images from a standardised database as PH2 dermoscopic database is used. Three different categories of images (benign tumours, normal moles and malignant melanoma) are selected and processed. Hair removal process is carried out to define a clear lesion from the skin images for feature extraction. Level set segmentation for lesion separation and feature extraction to classify the images into three different categories. Feature selection to configure the dominant and significant features. The dominant features are considered for classification with three different types of classifier such as Back propagation network, Pattern recognition network and Support vector machines. Performance parameters of the classifiers are obtained to determine an accurate classifier for these database dermal images.

Dermoscopic images are obtained from the database of skin cancer for the diagnosis system. PH2 database is a standardised and authorised database accepted by many dermatologists all over the world. Dermal images from these databases are used in the process of diagnosis. Images in the databases are obtained with the help of the dermoscope system with magnification power of 20× and resolution of 768 × 560 pixels. The images are acquired with a very high resolution and standard. Databases possess more than 2000 images of skin tumours which include melanomas, common nevi and benign tumours [2]. Out of which 1500 images are collected for three different types of skin tumours such as 500 from atypical nevus (benign tumours), 500 from malignant melanoma and 500 from common nevus (moles). Images in this database are not processed and normalised, it consists of all the features that the image possesses during a real time acquisition. Many Researches used these databases for the detailed study and analysis of the skin cancer images [2, 9, 10]. The database image is shown in Fig. 1.

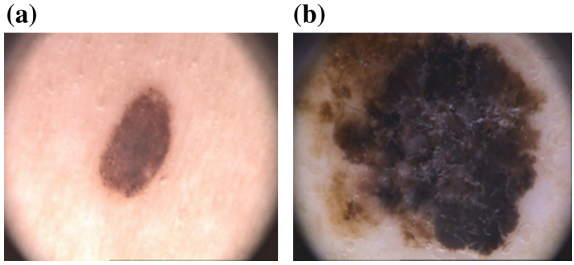

Fig. 1 Sample images of **a** benign tumour and **b** malignant melanoma. *Source* PH2 database

Melanoma lesions are irregular and asymmetrical. In the proposed methodology, dermal images from the PH2 database of three categories are processed. Dermal images are pre-processed through dilation. Segmentation is carried out with contour level set method and the features are extracted from the lesions. Random subset feature selection

technique is defined to obtain significant features. With these significant features, classification is carried out. Three different classifiers (BPN, PNN & SVM) are used to categorise three different types of dermal images. Therefore the proposed methodology is shown in Fig. 2.

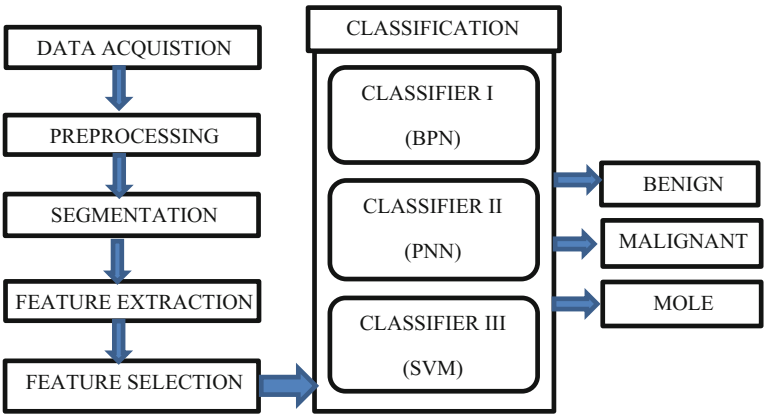

Fig. 2 Proposed methodology for diagnosis of dermal images

Pre-processing technique such as Dilation is carried out to remove the hair cells because the lesions are covered by the hair cells. Hair cells obstruct the clear vision of the lesion in the dermal image. In this process the original RGB image converted into grayscale image and hair cells are removed by morphological operation called grayscale dilation in which structural function is defined over the image. This enables better segmentation of lesion and extraction of features from the dermal images. Thus classification is more effective. Grayscale dilation is done with the help of the dilation operation as shown in Eq. 1 with $f(x)$ as image function and $b(x)$ as structuring function in Euclidean space (E).

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

Segmentation is mainly to separate the lesion from the background to extract features. In this process, contour based level set segmentation method is defined for separation of lesion from the skin surface. In this technique, Level set function determined for the curvature of the lesions in the grayscale dilated images and defines the lesion curvature in a binary image. Superimposition burning of the binary image over the original image derives the lesion without any background. The lesion image is used for feature extraction. Contour level set method is described below in Eq. 2 with Ψ as level set function.

$$\frac{\partial \Psi}{\partial \mathrm{t}} = v|\nabla \Psi| \tag{2}$$

In feature extraction process, totally fifteen features are derived. They are Morphological features (2 parameters), Diagnostic clinical features (Asymmetry, Border irregularity, Colour variation and Diameter) of seven parameters, Statistical features and GLCM (Gray Level Co-occurrence Matrix) features (5 parameters). Clinical features described by the dermatologists as ABCD features which helps in the identification and determination of the different types of skin tumours. These features involve asymmetry index, border irregularity, colour variance and diameter that exactly and specifically explain the nature of the lesions or tumours.

Asymmetry index. Asymmetry Index defines that the shape of one half does not match the rest half. The severity of the skin cancer depends on asymmetry degree of a skin lesion. Biaxial asymmetry of the lesion helps more in diagnosis. So, asymmetry around both minor and major axes needs to be calculated. Asymmetry Index (AI) is calculated as shown in Eq. (3) with $\Delta Amax$ and $\Delta Amin$ correspond to the non-overlapping areas along major and minor axis respectively. A is the total area of the lesion.

$$\mathrm{AI} = \frac{\Delta\mathrm{Amax} + \Delta\mathrm{Amin}}{2 * \mathrm{A}} \tag{3}$$

Border irregularity. Irregularity of the lesion boundaries termed as border irregularity. The edges with pigmentation may extend into surrounding skin. Malignancy can be catalogued from benign one by analysing lesions boundary. Malignant lesions are more irregular than benign. Two parameters are used to define the border irregularity of the lesions. Compactness Index (CI) measures roundness in a two dimensional object. Index is sensitive to the noise defined around the boundary of the lesion. It is defined in Eq. (4) with P as perimeter of lesion and A as area of the lesion

$$\mathrm{CI} = \frac{\mathrm{P}^2}{4\pi\mathrm{A}} \tag{4}$$

Circularity Index measures the circular nature of the lesion or defines the outline based on the curvature of the lesion. It is defined by Eq. (5)

$$\text{Circularity index} = \frac{4\pi\mathrm{A}}{\mathrm{P}^2} \tag{5}$$

Colour variation. Colour variance parameter analyses the colour distribution of lesion. It checks variation of colour from the centre to its boundary. Colour distribution throughout the lesion in the skin is defined with mean and standard deviation that is 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 has more diameter than benign or nevus samples (larger than six millimetres or about a quarter inch for malignant melanoma).

Gray level Co-occurrence matrix 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 Eqs. (6)–(10) with i and j as gray levels.

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

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \left\{ G \sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j) \right\}, |i-j| = n \tag{6}$$

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

$$\text{Correlation} = \sum_{i=1}^{G} \sum_{j=1}^{G} (\{i \times j\} P(i,j) - \{\mu x \times \mu y\}) / \sigma x \times \sigma y \tag{7}$$

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

$$\text{Entropy} = -\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \times \log(P(i,j)) \tag{8}$$

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

$$\text{Energy} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (P(i,j))^2 \tag{9}$$

Homogeneity among the gray level pixels of the image are described in Eq. (10).

$$\text{Homogeneity} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left(1/1 + (i-j)^2\right) [P(i,j)] \tag{10}$$

The fifteen features undergo feature selection process to obtain significant and dominant features for effective classification. Feature selection technique is mainly to obtain dominant features which completely define the characteristics of the lesion in the image. Dominant features for classification process are determined using Random Subset Feature Selection (RSFC) technique. Random Subset Feature Selection (RSFS) is a feature selection method in which random subset of features is used to determine the significant features. 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. Each feature is evaluated in RSFS in terms of its average usefulness in the context of many other feature combinations. Random subsets of fifteen features are obtained and the probability of all subsets is compared using k-NN algorithm. Seven features such as Asymmetry Index, Colour Variation, Compact Index,

Mean, Energy, Contrast and Entropy with the 99% of probability are described as the dominant features. With these features, classification of images is carried out.

Three types of classifiers such as back propagation network, pattern recognition network and support vector machines are used to differentiate the different categories of images. Efficiency of the classifiers are studied and analysed with the help of the performance parameters of classification.

Back propagation neural network (BPN) is useful for complex pattern recognition and mapping functions. In BPN, a predefined set of input and output pair is used for learning with the help of two phase propagate adapt cycle [11]. The input layer is applied with stimulus which propagates to the upper layers to define a output unit. Backward flow of the error signals computed for each output unit to the input unit.

Pattern recognition neural network mainly focuses on the recognition of patterns and data regularity. Pattern recognition is supervised learning that are probabilistic in nature. Statistical inference in the pattern recognition provides a best result. The aim is to define the probability of each target of the training sample with the particular input. The probability recognises the complex patterns.

Support vector machines (SVM) are supervised machine learning algorithms or models. SVM is the representation of points that maps to form separate divisions and a clear boundary is defined called decision boundary [12]. In this training sample forms a hyper plane in D-dimensional space in such a way that the margin separates the positive and negative samples. Multiclass support vector machine in which different classes is optimised with the kernels. In multiclass SVM decision boundary between all the classes in comparison with other classes ids formed.

Dominant features are considered for classification using three different classifiers. Classification in which both training and testing phase occurs. Confusion matrix is obtained for each classifier in order to learn the performance of the classification algorithm. Performance of the three classifiers 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.

Accuracy is defined as the observational error that describes the trueness of the classification function. Precision defines the statistical variability of random errors and related to the reproducibility and repeatability state of classification. Accuracy and precision are defined in terms of TP, TN, FN & FP is shown in Eqs. (11) and (12)

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{P} + \text{N}}, \quad \text{P} = \text{TP} + \text{FN}, \ \text{N} = \text{FP} + \text{TN} \tag{11}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{12}$$

Sensitivity and specificity are classification performance tests which involves statistical measures. Sensitivity and specificity measures the positive and negative proportions that are correctly defined respectively. They are described in Eq. (13).

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{13}$$

$$\text{Specificity} = \frac{\text{FP}}{(\text{FP} + \text{TP})} \tag{14}$$

Performance parameters are used to define the effective and efficient classification nature of the three different classifiers. Analysis of variance (ANOVA) is a collection of statistical models that is used for analysis of difference between the group means and other associated process like variations between or among the groups. 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 is obtained. This defines the efficient classification process. *P* value describes the significance of variations between the two samples. Honestly significant difference is defined using Tukey test which is a multiple statistical comparison procedure. Thus the best classifier for the diagnosis of skin images is obtained.

3 Results and Discussions

In the proposed method, the PH2 database dermoscopic images are used for the computer aided diagnosis system development process. 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 grayscale images as shown in Fig. 3.

Grayscale dilation process is carried out to remove the hair cells for accurate feature extraction and classification. In this morphological operation, disk structuring element is used as a function over the image to obtain a pre-processed image. Dilation processed images are shown in Fig. 4.

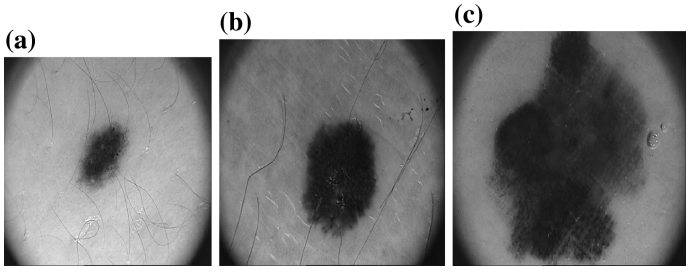

Fig. 3 Original images **a** normal mole, **b** benign tumour, **c** malignant melanoma

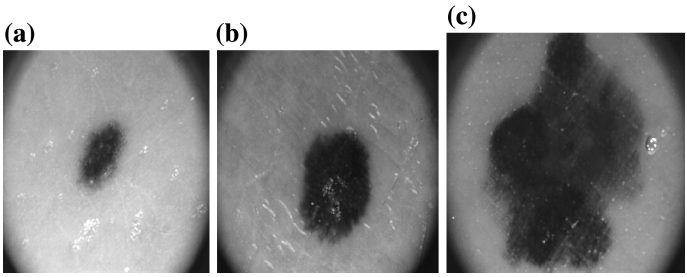

Fig. 4 Dilation processed images **a** normal mole, **b** benign tumour, **c** malignant melanoma

Contour based level set method is used in segmentation of the lesion from the images. 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. Segmented images are defined in Fig. 5. Superimposition of the mask over original image occurs which is defined in Fig. 6.

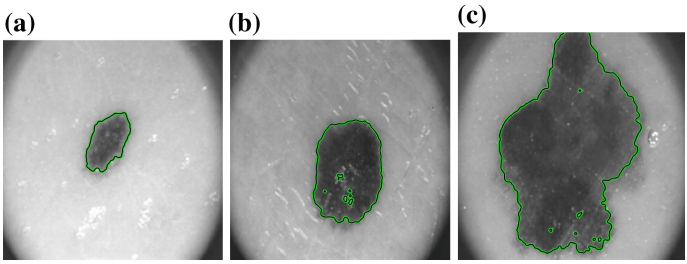

Fig. 5 Contour based level set segmented images **a** normal mole, **b** benign tumour, **c** malignant melanoma

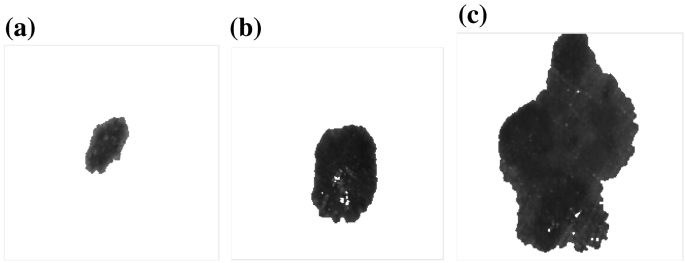

Fig. 6 Superimposed segmented images **a** normal mole, **b** benign tumour, **c** malignant melanoma

Feature extraction is carried out in the segmented lesion image. Fifteen features are extracted including the diagnostic clinical features, morphological and statistical features. Asymmetry Index, border irregularity, colour variation and diameter are the clinical features obtained from the segmented lesion. These features undergo selection process from which dominant features are derived for classification. Feature selection is carried out based on Random subset feature selection process. Seven features are described as dominant features to classify the three categories of dermal images. Random subset of features is determined and the probability of each random subset is calculated. Based on the probability a subset of random features is obtained as significant features. In this process from the random subset of fifteen features, seven significant features are determined with 99% of probability using k-NN algorithm. Significant nature of features are further analysed with the statistical values such as mean and standard deviation (SD). These statistical values of the seven significant features obtained as a result of random subset feature selection process is described in Table 1.

Table 1 RSFS based selected features (seven features)

Random subset feature selection (RSFS) based significant features							
Classes		Normal		Benign		Malignant	
		Mean	SD	Mean	SD	Mean	SD
Seven dominant 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
	Asymmetry index	47.16	2.448	46.56	2.934	40.48	8.785

The significant features selected are defined for the classification process. Three different classifiers are used in which one type of classifier is based on machine learning and two are neural network based classifiers. Classifier 1 that is the back propagation network in which the both training and testing occurs. Output unit is formed corresponding to the stimulus applied to each input unit. Error signal formed along with the output unit has a backward flow. Thus seven significant features are framed as the input samples with defined output. Confusion matrix is defined with true negative (TN), true positive (TP), false negative (FN) and false positive (FP) for all the three categories of dermal images which is shown in Table 2.

Table 2 Confusion matrix for classifier 1 (BPN)

		Predicted class		
		Normal	Benign	Malignant
Actual class	Normal	**446**	54	0
	Benign	16	**477**	7
	Malignant	0	8	**492**

Classifier 2 is the pattern recognition mainly defined to recognise complex patterns and mappings. Pattern recognition is a supervised learning in which output unit to be obtained is predefined along with the input unit. Based the predefined units the recognition process occurs and also depends on the probability of the complex patterns. In this seven features are subjected for training and testing process with hidden layer to obtain a confusion matrix as shown in the Table 3.

Table 3 Confusion matrix for classifier 2 (PNN)

		Predicted class		
		Normal	Benign	Malignant
Actual class	Normal	**476**	24	0
	Benign	22	**468**	10
	Malignant	0	0	**500**

Classifier 3 is Support vector machine (SVM) in which a margin of separation so called decision boundary separates the positive and negative classes of the input samples with predefined values. SVM is a supervised learning process. Multi-class SVM is used in which all the three categories of dermal images are classified based on the predefined values set as a target for the input unit. Confusion matrix is shown in Table 4 that describes the classification performance of SVM.

Table 4 Confusion matrix for classifier 3 (SVM)

		Predicted Class		
		Normal	Benign	Malignant
Actual class	Normal	**483**	17	0
	Benign	4	**494**	2
	Malignant	0	4	**496**

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 categorises the three different classes of dermal images. Percentage of each parameter describes the accurate and efficient classifier for dermal image diagnosis. Efficiency of classification can be

increased by increasing the number of hidden units in the neural network and by changing the kernel function in the machine learning classifier such as support vector machine. With the increase in the hidden units or kernels, the classification performance increases which is shown in Table 5. The hidden units or kernels are increased from 10, 20, 30 & 40 which show changes in the efficiency of the classification process.

Table 5 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

Performance parameters of the classification process are described in percentage for the hidden units or kernels of value 40. These parameters are obtained with higher efficiency value is given below in Table 6.

Table 6 Percentage of performance parameters of classification

	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

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 defined to be more efficient compared to other classifiers. Performance parameters of the multiclass SVM classifier prove to be more efficient with the help of results.

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 ten trials are carried with the three classifiers for which accuracy, precision,

specificity and sensitivity are calculated. With these values obtained for the ten trials, the ANOVA test is performed. One way ANOVA test reveals that the *P* value <0.01 or <0.05 then it is 99 or 95% of confidence level respectively for the performance parameter measures for ten trials. Consolidated results of one way ANOVA test is described in Table 7.

Table 7 Consolidated results of one way ANOVA test

Parameters	BPN	PNN	SVM	*P*
Accuracy	93.8	95.9333	98.2	<0.0001
	94.3333	96.2667	98.4667	
	94.6	97.5333	98.6667	
	94.4	96.6667	98.7333	
	94.6133	96.6	98.1333	
	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	94.4480	96.30001	98.53333	
Precision	0.9399	0.9451	0.9823	<0.0001
	0.9454	0.9625	0.9851	
	0.9482	0.9756	0.9867	
	0.9465	0.9767	0.9875	
	0.9454	0.9765	0.9814	
	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	0.9910	<0.0001
	0.9717	0.9814	0.9923	
	0.973	0.9877	0.9933	
	0.9720	0.9883	0.9937	
	0.9717	0.988	0.9907	
	0.973	0.986	0.9923	
	0.974	0.9924	0.9933	
	0.9720	0.9883	0.9937	
	0.9717	0.988	0.9927	
	0.973	0.9903	0.9937	
Mean stats	0.9721	0.98632	0.9927	

(*continued*)

Table 7 (*continued*)

Parameters	BPN	PNN	SVM	*P*
Sensitivity	0.938	0.9453	0.982	<0.0001
	0.9433	0.9627	0.9847	
	0.946	0.9753	0.9867	
	0.944	0.9767	0.9873	
	0.9433	0.976	0.9813	
	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 8 Consolidated results of Tukey's test

Parameters	BPN	PNN	SVM	Tukey's test
Accuracy	93.8	95.9333	98.2	HSD[0.05] = 0.01 HSD[0.01] = 0.01 M1 vs M2 $P < 0.01$ M1 vs M3 $P < 0.01$ M2 vs M3 $P < 0.01$
	94.3333	96.2667	98.4667	
	94.6	97.5333	98.6667	
	94.4	96.6667	98.7333	
	94.6133	96.6	98.1333	
	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	94.4480	96.30001	98.53333	
Precision	0.9399	0.9451	0.9823	HSD[0.05] = 0 HSD[0.01] = 0.01 M1 vs M2 $P < 0.01$ M1 vs M3 $P < 0.01$ M2 vs M3 $P < 0.05$
	0.9454	0.9625	0.9851	
	0.9482	0.9756	0.9867	
	0.9465	0.9767	0.9875	
	0.9454	0.9765	0.9814	
	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	

(*continued*)

Table 8 (*continued*)

Parameters	BPN	PNN	SVM	Tukey's test
Specificity	0.969	0.9728	0.9910	HSD[0.05] = 0.01 HSD[0.01] = 0.01 M1 vs M2 $P < 0.01$ M1 vs M3 $P < 0.01$ M2 vs M3 $P < 0.01$
	0.9717	0.9814	0.9923	
	0.973	0.9877	0.9933	
	0.9720	0.9883	0.9937	
	0.9717	0.988	0.9907	
	0.973	0.986	0.9923	
	0.974	0.9924	0.9933	
	0.9720	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	HSD[0.05] = 0.49 HSD[0.01] = 0.62 M1 vs M2 $P < 0.01$ M1 vs M3 $P < 0.01$ M2 vs M3 $P < 0.01$
	0.9433	0.9627	0.9847	
	0.946	0.9753	0.9867	
	0.944	0.9767	0.9873	
	0.9433	0.976	0.9813	
	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	

Tukey's test defines the honestly significant difference (HSD) between the group means and comparison of group variations. HSD also used to enumerate the efficiency of classification. The results of Tukey's test are shown in Table 8. Thus one way ANOVA and Tukey's test explains a best conclusion for the efficient classification process to be support vector machine.

4 Conclusion and Future Work

The incidence of skin cancer is increasing among the 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 is necessary. In this methodology, database images of three different categories such as Common mole, benign tumour and malignant melanoma undergo image analysis process such as hair detection and removal, segmentation of the lesion, feature extraction, feature selection and classification. Classification is carried out with three different classifiers such as back propagation network, pattern recognition network and support vector machine. Efficiency and performance of the classification process of

each classifier is determined using the performance parameters from the confusion matrix. One way ANOVA test is performed to define the significant classification process. Support vector machine (SVM) of 98% is described to be efficient for classification of dermal images. From the results, a computer aided diagnosis module is developed which classifies the three types of skin tumours.

Future work focuses on the development of a real time diagnostic tool is required which can help the dermatologists more effectively in early detection and diagnosis. Further development in the work includes formation of Indian database for skin tumours and extending the diagnosis for real time skin tumour images of different categories.

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