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Combined empirical mode decomposition and texture features for skin lesion classification using quadratic support vector machine

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Abstract

Purpose: Basal cell carcinoma is one of the most common malignant skin lesions. Automated lesion identification and classification using image processing techniques is highly required to reduce the diagnosis errors.

Methods: In this study, a novel technique is applied to classify skin lesion images into two classes, namely the malignant Basal cell carcinoma and the benign nevus. A hybrid combination of bi-dimensional empirical mode decomposition and gray-level difference method features is proposed after hair removal. The combined features are further classified using quadratic support vector machine (Q-SVM).

Results: The proposed system has achieved outstanding performance of 100% accuracy, sensitivity and specificity compared to other support vector machine procedures as well as with different extracted features.

Conclusion: Basal Cell Carcinoma is effectively classified using Q-SVM with the proposed combined features.

Keywords: Skin cancer classification, Basal cell carcinoma, Empirical mode decomposition, Riesz, Gray-level difference method, Support vector machine

Introduction

Skin cancer is known to be the most common type of all cancers. It is severe among the faired-skinned population in Europe, North America, and Australia. It is mainly caused by excessive sun exposure and the cosmic radiations encountered due to the ozone layer depletion [1]. Skin lesions are categorized generally into malignant (Cancerous) or non-malignant (Benign) lesions. Malignant lesions are either namely melanocytic lesions as Melanoma or non-melanocytic lesions as Basal Cell Carcinoma (BCC). Melanoma is considered as the deadliest type of skin tumors [1]. It is formed at the melanin (skin pigment) producing cells called melanocytes at the bottom of the epidermis (the outermost layer of skin).

Non-melanocytic malignant lesions include the squamous cell carcinoma (SCC) and the basal cell carcinoma (BCC). The BCC [2] can be initiated due to many reasons including exposure to the ultra-violet (UV) radiations, radiation therapy, immune-suppressing drugs and genetic inheritance that causes the formation of malignant tumors. Some forms of BCC can have the ability to invade and destroy nearby muscles, nerves and bones causing deformations.

Early diagnosis and treatment of cancerous tumors increases the recovery chances. However, the traditional diagnostic procedures that depend on the medical expert's manual examination encounter difficulties and human error due to the high resemblance of the lesions at their early stages. Moreover, biopsy samples may cause complications in some cases as inflammation, bleeding or even spreading the lesion. Recent medical imaging techniques, such as in vivo dermoscopy integrated with the aid of machine learning algorithms provided a

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powerful tool in terms of accuracy and processing time for early skin cancer diagnosis without any side effects on the patient. Generally, computer-aided medical image analysis system for automated cancer tumour consists of four consecutive processes, namely image acquisition and pre-processing, segmentation, feature extraction and selection, finally, lesion classification using machine learning algorithms.

Several researchers are motivated to develop algorithms for skin cancer detection and classification based on machine learning. Ganster et al. [3] proposed a system for computerized Melanoma detection using several extracted features describing the size and shape of the skin lesion. Afterward, k-nearest neighbors algorithm (k-NN) classifier has been applied that achieved 96% accuracy, 87% sensitivity, and 92% specificity. Yuan et al. [4] proposed a decision support system using support vector machine (SVM) for determining whether a skin lesion is benign or malignant relying only on texture analysis of the lesion pigmentation characteristics which achieved overall accuracy of (86.9%). Lau and Al-Jumaily [5] introduced a classification system based on 3-layer back-propagation ANN based using discrete wavelet transform (DWT) features. The results illustrated recognition accuracy of 89.9% compared to auto-associative neural network of 80.8% accuracy. Alcón et al. [6] developed a system for skin lesion images obtained by digital cameras used a decision support parameter that combined the image classification outcome with patient's personal history that includes: skin type, age, gender, and affected body part. This classification system resulted in image classification specificity of 68%, sensitivity of 94%, and accuracy of 86%. Elgamal [7] employed principle component analysis to select the most essential features extracted by DWT. Afterward, for classification process, two classifiers have been developed, namely the feed forward back-propagation ANN and k-NN based classifier that achieved accuracy rates of 95 and 97.5%; respectively.

The preceding studies clarified that no previous work has been conducted using the bi-dimensional empirical mode decomposition (BEMD) or gray-level difference method (GLDM) texture features for skin cancer classification. Consequently, the proposed methodology classified two types of lesions, namely malignant BCC and benign Nevus using a combination of the BEMD and GLMD. In the present work, OTSU threshold of the DWT is employed for segmenting the acquired pre-processed image. Afterward, features are extracted by using the proposed combination of BEMD followed by Riesz transform along with the GLDM texture features. The extracted features are classified using the quadratic support vector machine (Q-SVM) and compared with the performance of other SVM methods.

Finally, performance metrics are calculated for system evaluation.

The structure of the remaining sections is as follows. “[Methodology](#)” section introduces the proposed methodology and details of the used techniques. “[Experimental results](#)” section illustrates the system performance and results. Finally, “[Conclusion](#)” section concludes the present study.

Methodology

The proposed work followed the following procedure, namely (i) hair removal using DullRazor software, (ii) segmentation using OTSU thresholding over the image, (iii) feature extraction using BEMD-Riesz transform features combined with texture GLDM features, and finally (iv) quadratic SVM for classification. Afterward, the system performance is validated using a dataset of 56 dermoscopy images including 29 basal cell carcinoma and 27 nevus images. This dataset is publicly available from the International Skin Imaging Collaboration (ISIC) archive. Figure 1 illustrated sample images from the two classes under concern in the present work.

Image pre-processing

The main objective of this stage is improving the acquired images quality by filtering out any unwanted distortions, such as hair, blood vessels or skin pigments as well as compensating the non-uniform illumination problem if present. In this work, the well-known DullRazor technique [8] is used to suppress the unwanted hairs in the image. Then, the pre-processed images are converted from red–green–blue (RGB) color planes into grayscale for further segmentation process.

Segmentation process

Segmentation process aims to separate the lesion area from the surrounding skin by identifying the lesion boundaries that considered the region of interest (ROI). Generally, different methods can be employed for the segmentation process, such as threshold based- [9], region based- [9], and cluster based- [10] segmentation.

In the current methodology, the applied segmentation method depends mainly on Otsu's [11] global thresholding technique due to its simplicity. However, Otsu's technique has some limitations because of its high dependence on the image histogram. It may have inefficient results with images that contain histogram of weak peaks. Hence, the DWT is first applied on the image to enhance the performance of Otsu's technique. The DWT is used to extract the low frequency components representing the contour's boundary and the high-frequency component representing the detail. Thus, the low-frequency components are reconstructed, while the

Fig. 1 Sample images from the dataset: **a** Basal cell carcinoma; **b** nevus

redundant information is removed effectively. Then, Otsu algorithm is used for segmenting the ROI as proposed in [12].

Discrete wavelet transform

Discrete wavelet transform (DWT) [13] decomposes an image into its low frequency components and high frequency components. The high frequency component carries the image detail information (i.e. Horizontal, vertical and diagonal details). If those details have negligible values, they can be set to zero without significant change in the image for filtering purpose. The low frequency component keeps the main image characteristics (approximation information) that show the general trend of pixel values. In the present work, the input image is applied to the wavelet decomposition system shown in Fig. 2.

Figure 2 illustrates that the output after each filtering process is down-sampled by two. According to Nyquist sampling rate, only half of the samples are needed for perfect reconstruction of the signal. The reconstruction process will follow the same system in Fig. 2, but in the opposite direction where the output of each filtering stage will up-sampled by two. The resulting DWT component of an image after one decomposition level is shown in Fig. 3. This process can be further repeated over the sub-image of each quadrant.

Otsu's thresholding criterion

Otsu's criterion [11] aims to automatically select the best threshold that splits the pixels in the image into two classes, the foreground class and the background class. The selected threshold is the one that maximizes the

Fig. 2 One level of DWT decomposition system

inter-class variance, while, each individual class should have as low variance as possible. For a given image that has L gray levels $\{0, 1, 2, \dots, L - 1\}$ histogram, Otsu's thresholding will split the pixels into two classes C_1 and C_2 by finding the threshold T such that,

$$C_1 = \{(x, y) | I(x, y) \leq T\} \quad (1)$$

$$C_2 = \{(x, y) | I(x, y) > T\} \quad (2)$$

where $I(x, y)$ is the gray-level intensity of the pixel at position (x, y) . Let n_i be the number of pixels in the i^{th} gray level, the total number of image pixels be n . Then, the probability of occurrence of the level i is defined as:

$$P_i = \frac{n_i}{n} \quad (3)$$

The probability that a certain pixel belongs to a class C_1 or class C_2 is given respectively by Eqs. (4) and (5) as:

$$P_1 = \sum_{i=0}^T P_i \quad (4)$$

$$P_2 = \sum_{i=T+1}^{L-1} P_i \quad (5)$$

Thus, the class-conditional mean of each class can be computed for class C_1 and C_2 respectively by Eqs. (6) and (7) as:

$$m_1 = \frac{\sum_{i=0}^T i \cdot P_i}{P_1} \quad (6)$$

$$m_2 = \frac{\sum_{i=T+1}^{L-1} i \cdot P_i}{P_2} \quad (7)$$

The image global mean m_G , global variance σ_G^2 and the between class variance σ_B^2 are expressed respectively as:

$$m_G = \sum_{i=0}^{L-1} i \cdot P_i \quad (8)$$

$$\sigma_G^2 = \sum_{i=0}^{L-1} (i - m_G)^2 \cdot P_i \quad (9)$$

$$\sigma_B^2 = P_1 \cdot (m_1 - m_G)^2 + P_2 \cdot (m_2 - m_G)^2 \quad (10)$$

The ratio $\frac{\sigma_B^2}{\sigma_G^2}$ is considered the suitable measure of the separability between both classes. So, Otsu's technique aims to choose the threshold T that maximizes this ratio for superior segmentation. Afterwards, feature extraction process is carried out to extract the significant features from the segmented lesion.

Feature extraction

Feature extraction process aims to obtain features from the ROI to describe various attributes of the image. These properties can be morphological features that depends on the lesion visible parameters or statistical as the features obtained from mathematical domain transformations.

As far as researched about previous skin cancer classification studies, BEMD features were not used for skin cancer features extraction, most probably due to their ineffectiveness in such case. Consequently, in the current work, a combination of BEMD-Riesz features and GLDM texture features is used to provide significant features for enhancing the classification process compared to the use of either of them separately. Subsequently, the BEMD-Riesz features are extracted by applying BEMD on the segmented image to obtain the Intrinsic Mode Functions (IMFs). Local energy and local phase features are extracted from each IMF by Riesz transform. In addition, the GLDM texture features are also obtained.

Bi-dimensional empirical mode decomposition and Riesz transform

In this work, Bi-dimensional Empirical Mode Decomposition (BEMD) is applied as the first step in

Hilbert–Huang-Transform (HHT). For a 2-D image $f(x, y)$ of M columns and N rows, where $x = 1, 2, \dots, M$ and $y = 1, 2, \dots, N$ the BEMD sifting process illustrated in Fig. 4, decomposes the image I into n IMFs and a residual r_j as expressed in the following equation:

$$I = f(x, y) = \sum_{j=1}^n IMF_j(x, y) + r_j(x, y) \quad (11)$$

The obtained IMF from sifting process must satisfy two conditions [14], namely: (i) each IMF must have the number of zero crossings and of extrema one difference at most, and (ii) each IMF must be symmetric with respect to its mean (i.e. has zero mean). The flowchart of the BEMD sifting process is illustrated in Fig. 4.

Figure 4 demonstrated that the steps of the sifting process which are shown as follows.

Algorithm: BEMD sifting process

Start

Convert the original RGB image to a gray-scale image $I = f(x, y)$

Identify the minima and maxima of the image I using connected neighbourhood window method or morphological reconstruction based on geodesic functions as dilation and erosion

Compute the 2-D envelope by connecting both the maxima points and minima points separately using interpolation techniques (e.g. spline interpolation)

Take the average (local mean m_1) of both the minima and maxima envelopes

Calculate the detail d by subtracting the local mean m_1 from the image I

Evaluate whether the detail satisfies the IMF conditions or not.

If the detail doesn't satisfy the IMF conditions

input the details to the next loop

Else (if the detail satisfies the conditions)

consider them an IMF

Subtract the detail d from the original image I and the residue

$I_{res} = I - d$ will run through this process again, until the pre-determined stop criterion is reached

End if

Stop

The stop criterion determines the stopping condition of the sifting process which is achieved by limiting the size of the standard deviation (SD), SD is calculated from the two consecutive sifting outputs $IMF_{j(i-1)}$ and IMF_{ji} for the j th mode as:

$$SD = \sum_{k=0}^M \sum_{l=0}^N \left[\frac{|(IMF_{j(i-1)}(k, l) - IMF_{ji}(k, l))|^2}{IMF_{j(i-1)}^2(k, l)} \right] \quad (12)$$

Usually, EMD is used for decomposing a signal into its IMF components. Afterward, Hilbert spectrum analysis

(HSA) is applied on each IMF to obtain the analytical signals. Based on the analytical signal, local features including the amplitude, phase, frequency and orientation can be extracted.

The HHT process can be expressed as follows to obtain the analytical signal using Hilbert transform for extracting the local features. The Hilbert transform f_{Hi} of a one-dimensional signal f is expressed as [14]:

$$f_{Hi}(x) = f(x) \otimes \frac{1}{\pi x} \quad (13)$$

The analytical signal f_A is the complex signal constituted by the conjugate pair of the original signal (as the real part) and the transformed signal (as the imaginary part), which is expressed by:

$$f_A(x) = f(x) + i f_{Hi}(x) \quad (14)$$

However, in the current work, images of 2-D signals are considered, thus, it is inadequate to use the 1-D Hilbert transform. Although, the presence of some other forms of Hilbert transform that aims to obtain 2-D analytical signal, such as: Partial Hilbert transform, total Hilbert transform, combined of partial and total Hilbert transform and combined partial and total Hilbert transforms in the quaternionic Fourier domain can be employed, however, they all have their drawbacks by either missing isotropy or not meeting the orthogonality condition required for the analytic signal [14].

The monogenic signal is a two-dimensional generalization of the 1-D analytic signal, where the Riesz transform replaces the Hilbert transform [14]. Riesz transform is developed as an approach for the 2-D analytical signal according to the theory of vector field [15]. The space representation of Riesz transform f_R for the vector $\vec{x} = (x_1, x_2)^T$ is:

$$f_R(\vec{x}) = -\frac{\vec{x}}{2\pi |\vec{x}|^3} \otimes f(\vec{x}) = h_2(\vec{x}) \otimes f(\vec{x}) \quad (15)$$

The Riesz transform expression in frequency domain is given by:

$$F_R(\vec{u}) = \frac{i\vec{u}}{|\vec{u}|} F(\vec{u}) = H_2(\vec{u}) F(\vec{u}) \quad (16)$$

where the transfer function H_2 of the Riesz transform is the 2-D generalization of the 1-D Hilbert transform and $\vec{u} = (u_1, u_2)^T$ is the two-dimensional vector. The monogenic signal is expressed as a complex 3-D vector:

$$f_M(\vec{x}) = f(\vec{x}) - (i, j) f_R(\vec{x}) \quad (17)$$

The local amplitude of $f_M(\vec{x})$ is given as:

$$|f_M(\vec{x})| = \sqrt{f_M(\vec{x}) \overline{f_M(\vec{x})}} = \sqrt{f^2(\vec{x}) + |f_R(\vec{x})|^2} \quad (18)$$

The monogenic signal phase is calculated by:

$$\phi(\vec{x}) = \arg(f_M(\vec{x})) \quad (19)$$

Consequently, from those preceding mathematical models; the BEMD based on Riesz transform is applied in the present work to extract the EMD features of the lesion images under concern. Furthermore, to improve the classification process, another set of features are extracted, which are the GLDM that are combined with the EMD features as proposed in the present work.

Gray-level difference method

GLDM was proposed in [16] as a texture feature extraction technique that depends on the occurrence of any absolute given difference in gray level of two pixels that are separated by displacement S . For any image $f(x, y)$, let the separation vector $S = (\Delta x, \Delta y)$ for which the absolute gray level difference $L_S(x, y) = |L(x, y) - L(x + \Delta x, y + \Delta y)|$. The probability density function for gray level difference i and separation vector S is defined by:

$$P(i|S) = \text{Probability}[L_S(x, y) = i] \quad (20)$$

In the current analysis, there are four possibilities for the vector S to be considered, which are $(0, d)$, $(d, 0)$, $(-d, -d)$, $(-d, d)$ that respectively stands for vertical, horizontal, and two cases of diagonal separations, where d is the inter-sample distance. For coarse textures, if S is small compared to the ROI size, the points at separation S should be close in gray level values, thus, $L_S(x, y)$ will be small. The exact opposite will be the case for fine textures. Some texture measures are usually calculated from each $P(i|S)$ as contrast, mean, entropy and angular second moment. In this proposal, the gray level similarity based on the GLDM for the four different separation vectors are calculated and used as the extracted features. However, as far as researched the GLDM has not been used in skin cancer detection.

Support vector machine

SVM is a machine learning model mainly used in data classification [17]. Each data point having X features is plotted in X -dimensional space having a coordinate for each feature as shown in Fig. 5 for $X = 2$. The main objective of SVM is to determine the best hyperplane that achieves the maximum separation of the given data classes (i.e. that has the maximum margin).

In most cases, the input feature space is not linearly separable. The SVM has a special ability to separate nonlinear

separable samples by using kernel functions. The kernel function takes low dimensional input space and transforms it to a higher dimensional space. Hence, it converts the non-separable problem to a separable problem. Kernel functions include: linear kernels, polynomial kernels as the quadratic and cubic function kernels and, Gaussian kernels as radial basis function (RBF) and it is also possible to develop other forms of kernels. Typically, the SVMs achieve the best classification results and the highest accuracy especially in high dimension data sets. In addition, the SVMs avoid the over-fitting problem encountered in neural networks [18]. The SVMs complexity is independent on the dimensions of the dataset, unlike the neural networks in which the number of hidden units increase with the increase in input dimensionality [19]. In the current work, the SVM is employed due to its advantages during the classification process compared to the neural networks.

Proposed algorithm

The proposed system for automatic skin lesion classification is demonstrated in Fig. 6.

Figure 6 demonstrated that the proposed skin cancer classification system follows the following steps, including image acquisition, pre-processing (hair removal), segmentation, feature extraction (using a proposed combined features group of BEMD-Riesz and GLDM features), and the classification using Q-SVM. Finally, performance metrics, such as the accuracy, sensitivity, specificity and F-measure are evaluated.

Performance metrics

Performance metrics are used for evaluating the system performance by measuring the accuracy, sensitivity, specificity and F-measure that are expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (21)$$

$$Sensitivity = TPR = \frac{TP}{TP + FN} \quad (22)$$

$$Specificity = TNR = \frac{TN}{TN + FP} \quad (23)$$

$$F\text{-measure} = \frac{2TP}{2TP + FP + FN} \quad (24)$$

where TP is the number of malignant BCC images correctly identified and FN is the number of benign Nevus images incorrectly identified as BCC. TN and FP counts for the number of benign Nevus images correctly and incorrectly identified; respectively.

Experimental results

In this section, the results of the proposed malignant Basal Cell Carcinoma and benign nevus classification system are reported. The dataset is used to evaluate the proposed system that mainly focuses on extracting combined features that are processed using Q-SVM. The proposed system is implemented using MATLAB R2015a on PC that has Intel-Core i5-2410 M 2.3 GHz processor with 8 GB of RAM running under MSWin.7 operating system. The hair removal pre-processing step output is illustrated in Fig. 7b, and the original image are shown in Fig. 7a.

Segmentation results

In the present work, 2D wavelet transform followed by Otsu's global thresholding technique is applied for image

Fig. 7 **a** Original image; **b** image after DullRazor hair removal

segmentation to detect the ROI indicating the skin lesion as illustrated in Fig. 8.

Afterward, the segmentation output representing the segmented lesion is used as input to the proposed combined feature extraction process.

Performance metrics comparative study

For the proposed combined features evaluation, receiver operating characteristics (ROC) curve is used, which evaluates the diagnostic ability of a classification system by plotting the true positive rate (TPR) against the false positive rate (FPR) for different discrimination thresholds. Figure 9 illustrates the ROC curve for different feature cases.

Figure 9 depicts that the best ROC plot is achieved with the combined features case, while, the worst case occurs when using the BEMD features only. Thus, the proposed features combination outperforms all cases for superior classification process.

In addition, the confusion matrix showing the TP, FP, TN, and FN counts for a certain classification problem is used to evaluate the used classifier. The confusion matrix in generally reports the classification performance metrics that are reported in Table 1 of the classification process for different feature combinations using Q-SVM. The four different feature cases are tested and compared separately, namely BEMD, BEMD-Riesz, GLDM, and the proposed combined BEMD-Riesz and GLDM. These features are extracted and used for the classification purpose. The results of the comparative study are reported in Table 1.

Table 1 establishes that for the best results are obtained with the proposed features combination. Since, the BEMD features are extracted by obtaining the mean of each of four IMFs, these features achieved the worst results. The BEMD-Riesz feature case has the local energy and local phase of each of the IMFs, thus it

Fig. 8 Sample skin lesion segmentation results: **a** input image, **b** segmentation mask, **c** output segmentation contour, and **d** segmented lesion

Fig. 9 The ROC curves of Q-SVM for different features cases: **a** BEMD only; **b** BEMD-Riesz; **c** GLDM; and **d** proposed combined BEMD-Riesz and GLDM

Table 1 Performance metrics by using quadratic SVM for different feature cases

Feature groups	Performance metrics			
	Sensitivity (%)	Specificity (%)	Accuracy (%)	F-measure
BEMD	73.60	64.50	68.10	0.6
BEMD-Riesz	77.70	85	80.90	0.8
GLDM	95.80	95.60	95.70	0.95
Proposed BEMD-Riesz GLDM	100	100	100	1

provides superior results compared to the BEMD. However, the four GLDM features that extracted from the mean of each of the four probability density functions, achieve superior performance compared to the BEMD only and the BEMD-Riesz only.

Comparative study of the SVM different kernel functions

To validate the superiority of the used kernel function of the SVM, a comparative study is conducted. The results of this comparative study are reported in Fig. 10.

Figure 10 establishes that the Quadratic SVM (Q-SVM) has the uppermost overall performance compared to the different used feature cases. Generally, the choice of the best kernel in any classification problem depends mainly on the dataset feature space. Generally, for non-linear separation problems, either RBF or polynomial kernels are usually used [20]. In this work, the results revealed that the best performing kernel for the used dataset is the quadratic polynomial SVM, which is the most common polynomial kernel as larger degrees tend to overfit. In addition, compared to other SVMs kernel functions, such as linear, cubic and Gaussian SVM, the Q-SVM achieved the superior performance with the proposed combined features with 100% accuracy.

Comparative study with other methods

Skin lesion classification and discrimination is a challenging task owing to the visual high-similarity between the different lesion classes, in which benign lesion classes has high-resemblance to malignant classes. Several studies and challenges have been conducted to resolve this problem. In order to, validate the performance of the proposed combined features method, a comparison is conducted with the results of previously published studies on the same ISIC dermoscopic images dataset. Mahmoud et al. [21] have proposed an automated system to discriminate between malignant melanoma and benign nevi, a total of 81 features were extracted from the colored lesion images. From each RGB channel histogram, six features were extracted, namely: mean, variance, kurtosis, skewness, entropy and energy. In addition,

about 21 features were extracted from the cooccurrence matrix of each RGB channel. The extracted feature vector dimensionality was then reduced using sequential feature selection. Afterthat, SVM was used for classification which resulted in 88.9% accuracy, 87.5% sensitivity and 100% specificity, for the test set of 42 images. In this proposal, the images were preprocessed using an adaptive median filter to remove any undesired artifacts prior to feature extraction. On the other side, in our proposed system only DullRazor hair removal is applied for pre-processing without including any other filters. Mahbod et al. [22] used 2000 ISIC dataset images for three classes namely, melanoma, seborrheic keratosis and benign nevi to train the proposed system that used convolutional neural networks as feature extractors which were then applied to SVM classifier. Finally, an accuracy of 84.7% was achieved. Table 2 reported a comparative study between the preceding related studies and the proposed method."

It is worth noting that in this proposed work, the high-resemblance different class images, namely BCC and benign Nevus are selected to evaluate the proposed classifier as the images of these two the two classes cannot be distinguished using the naked eye. Such characteristic in the used dataset complicated the classification process that is evaluated to measure the classifier's true ability to distinguish between different class images with similar features, which yielded to 100% accuracy using our proposed feature set. Hence, this reflects that for other lesion classes which have less similarity, can be classified using the proposed classifier with good performance

Table 2 Performance metrics comparison of different studies

Method	Used number of images	Classes	Number of selected features	Accuracy (%)	Sensitivity (%)	Specificity (%)
Morphological features with K-NN classifier [3]	270 training images 5363 test images	Three classes melanoma, dysplastic and benign lesions	21	96.9	87	92
Texture features only with 4 th degree polynomial SVM [4]	1000 training images, 22 test images	Two classes, malignant and benign lesions	200	86.9	–	–
Asymmetry, border, color and texture features merged with patient context knowledge with logistic model trees [6]	152 test images	Two classes, melanoma and benign nevus	55	86	94	68
Discrete wavelet transform components with K-NN classifier [7]	40 test images	Two classes, malignant and benign lesions	–	97.5	100	95
Histogram and cooccurrence matrix based features with SVM [21]	42 images	Two classes, malignant and benign lesions	2	88.9	87.5	100
Deep features using convolutional neural network feature extractor with SVM classifier [22]	2000 training images, 150 test images	Three classes, melanoma, seborrheic keratosis and benign nevi	–	84.7	–	–
Proposed combined BEMD-Riesz and GLDM with Q-SVM classifier method	46 training images, 10 test Images	Two classes, basal cell carcinoma and benign nevus	12	100	100	100

metrics, which can be studied in detail as a future work. In addition, as a future work the proposed system can be compared with the approach of Siuly et al. [23] that proposed an optimal allocation-based approach to extract the most effective features then, the least-square SVM classifier has been applied which outperformed the Naive Bayes methods.

Conclusion

Early and accurate diagnosis of skin cancer is essential to improve the treatment outcomes and to reduce the recovery time. So, in this work, an automated skin lesion detection system has been proposed as an early warning tool for skin lesion classification. The proposed system is mainly focused on Basal Cell Carcinoma detection/classification to help in increasing the recovery rates. The main contribution included the new combined features, namely the BEMD-Riesz local energy and phase combined the texture GLDM features.

These proposed features combination achieved superior performance using the Q-SVM when compared with BEMD, BEMD-Riesz, or GLDM features, when used separately. In addition, the extracted features that classified using Q-SVM achieved outstanding performance accuracy, sensitivity and specificity of 100%.

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