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Wavelet and Curvelet Analysis for Automatic Identification of Melanoma Based on Neural Network Classification

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Abstract — **This paper proposes an automatic skin cancer (melanoma) classification system. The input for the proposed system is a set of images for benign and malignant skin lesions. Different image processing procedures such as smoothing and equalization are applied on these images to enhance their properties. Two segmentation methods are then used to identify the skin lesions before extracting the useful feature information from these images. This information is then passed to the classifier for training and testing. The features used for classification are coefficients created by Wavelet decompositions or simple wrapper Curvelets. Curvelets are known to be more suitable for the images that contain oriented textures and cartoon edges. The recognition accuracy obtained by the two layers back-propagation neural network classifier tested in this experiment is 58.44 % for the Wavelet based coefficients and 86.57 % for the Curvelet based ones.**

Keywords: Segmentation; Wavelet decompositions; simple wrapper Curvelet; Back-Propagation Neural Network (BNN) Classifier.

I. Introduction

Australia has one of the highest skin cancer rates in the world at nearly four times the rates in Canada, the US and the UK. It has been estimated 115,000 new cases of cancer diagnosed and more than 43,000 people are expected to die from cancer according to Cancer council of Australian 2010. The Chair of Public Health Committee pronounced that, more than 430,000 cases treated for non-melanoma, and more than 10,300 people are treated for melanoma, with 1,430 people dying each year [1].

Skin cancer malignant melanoma is the deadliest form of skin cancer. It can be removed by simple surgery if it has not entered the blood stream. Melanoma can be recovered if diagnosed and treated in early stages. Early diagnosis is obviously dependent upon patient's attention and accurate assessment by a medical practitioner. Several published classification systems show accuracy rates ranging from 60%-92% [2] which coincides with the estimated rates obtained by general practitioners. These techniques were aiming to provide recommendation for non-specialized users. But the variations of diagnosis are high and there is lack of details about the test methods. One commercial product, Solar Scan by Polartechnics, has an accuracy rate of 92%. It is a complex system that takes high quality Dermoscopy, known as Epiluminescence Light Microscopy (ELM) images, and uses advanced image analysis techniques to extract a number of features for classification. It is unsuitable for use by unspecialized person. ELM needs an experienced professional to get the required image as opposed to the traditional imaging which is just a recording of what the human eye can.

Different approaches have been established to improve image processing results. The image processing for skin cancer detection consists of six main steps namely; (1) image acquisition step which used to collect database from different resources, (2) pre-processing to remove the fine hairs, noise and air bubbles, and unwanted objects, (3) Post-processing to enhance the shape of the image, (4) Segmentation to remove the healthy skin from the image and extract the region of interest contains the suspicious cell, (5) Feature extraction which extracts the useful information or image properties from the segmented images, (6) classification system to classify the image if it cancer or not. The classification system is usually supported by an intelligent classifier, such as neural network and support vector machine or others. A previous work of us in [3] [4] introduced an automatic early detection of skin cancer detection based on 3-layer back-propagation and auto-associative neural network classification. Wavelet based features were to train and test the classifiers. The results showed that back-propagation neural network has better accuracy than that of auto-associative neural network. The use of wavelet decomposition provides useful extracted feature for image processing but it could not develop the regularity of the edge curves [5] [6]. This is becoming one of the major short comings for feature extraction and thus finding of better feature extracting method while maintaining the 3-layers back-propagation neural network as a classification method is one of the main interests of this work. The rest of the paper is organized as follows: Sections 2, 3 and 4 explain different image pre-processing and post-processing steps that are used in the skin cancer detection framework. The segmentation methods used are clarified in section 5. The feature extraction step which involves the use of Wavelet and Curvelet transforms is thoroughly explained in section 6. Section 7 explains our classifier, the Back-Propagation Neural Network (BNN) in detail. Section 8 evaluates our proposed framework and sections 9 and 10 state our conclusions and the future work directions, respectively.

II. Image Acquisition

The image databases we use contain both digital photo and Dermoscopy images. These images were collected from Sydney Melanoma Diagnostic Centre in Royal Prince Alfred Hospital and Internet websites. Total 448 images are collected; these images include digital malignant melanoma images and digital benign melanoma images. The images separated into four groups to test the classification accuracy corresponding for each group. The database images are obtained from different sources and the size of the images is non-standard. The first step in the process is to resize the image to have a fixed width (360) but variable size of height. The second step is to remove the background noise from the pictures to increase the accuracy of the detected images.

III. Image Pre-Processing

Skin cancer images often contain irrelevant objects such as fine hairs, noise and air bubbles around the lesion. These objects are not part of the cancer cell and would reduce the accuracy of the border detection or segmentation and increase the computational time. In [3] and [4], we overcame these problems using pre-processing techniques to remove the unwanted features on the skin and to enhance the shape of image.

Karhunen-Loève (KL) transforms histogram equalization and different kinds of filters were used to achieve these goals. In addition, contrast enhancements which can sharpen the image border and improve the accuracy for segmentation were also used. Wavelets de-noise two-dimensional Biorthogonal (bior), which is advanced linear wavelet used in image reconstruction and decomposition [3] [4] was used to remove the background noise from the picture.

A. Black frame removal

Dermoscopy images often contain black frames that are introduced during the digitization process. These frames need to be removed because they might interfere with the subsequent border detection steps. In order to determine the darkness of a pixel with (R, G, and B) coordinates, the lightness component of the HSL color space [7] is utilized:

$$L = \frac{\max(R, G, B) + \min(R, G, B)}{2} \qquad (1)$$

In particular, a pixel is considered to be black if its lightness value is < 20 in equation (1). Using this criterion, the image is scanned row-by-row starting from the top. A particular row is labeled as part of the black frame if it contains 60% black pixels. The top-to-bottom scan terminates when a row that contains less than the threshold percentage of pixels is encountered. The same scanning procedure is repeated for the other three main directions.

B. Image smoothing

In order to remove unwanted features from images, firstly some pre-processing has to be applied to remove the fine hairs, noise and air bubbles on the skin facilitating image segmentation using Wiener and Median filters. Wiener filter purposed to reduce the amount of noise presented in a signal by comparison with an estimation of the desired noiseless signal. It work based on neighboring pixels of size m-by-n to estimate the local image mean and standard deviation. The additive noise (Gaussian white noise) power is assumed to be noise [8].

Next step is image smoothing by Median filter. It is one of the most common smoothing filters in the literature. Median filtering with a mask of appropriate size can eliminate most of the artifacts in images [9] [10]. Median filtering is a standard nonlinear signal processing technique developed by Turkey [11] for suppressing the noise in the image by removing the outliers that are the extreme pixel values.

Median filter can be used to preserve edge, remove the noise produced by the image capturing and remove the fine hairs. The size of filter windows is calculated based on method from [12] [13]. The equation refers to a typical size of 768x512 pixels. Note that the mask size should be proportional to the image size for optimal results. In this study, the mask size n is determined by:

$$n = floor\left(5\sqrt{\left(\frac{M}{768}\right)\cdot\left(\frac{N}{512}\right)}\right) \qquad (2)$$

Equation (2) is based on the observation that M and N refer to the dimensions of resized image. n = 5 is a good choice and it proved working when the image size changes, this is reflected on the mask size proportionally.

IV. Image Post-Processing

The post- processing enhances the shape of the image. In this work, Histogram equalization (HE) algorithm was utilized. It is a smart contrast enhancement technique which stretches the dynamic range of the image histogram and resulting in overall contrast improvement. Fig. 1 shows the result of segmentation by threshold with Gray scale Histogram Equalization (GHE) (bottom right) and Local Histogram Equalization (LHE). The LHE (bottom left) sharpen the lesion but also reduce the surrounding detail.

V. Image Segmentation

Segmentation means the process of partitioning a digital image into multiple segments (sets of pixels). It is used to locate objects and boundaries (lines, curves, etc.) in images. Image segmentation is also the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics [12]. Shown practical example for Medical Imaging (Locate tumors and other pathologies, Measure tissue volumes, Computer-guided surgery, Diagnosis, Treatment planning, Study of anatomical structure). In this paper, two segmentation methods: thresholding Region of Interest (ROI) and Statistical Region Merging (SRM) have been implemented, It work based on the information from the clinical result that noticed lesion is usually darker than the human skin.

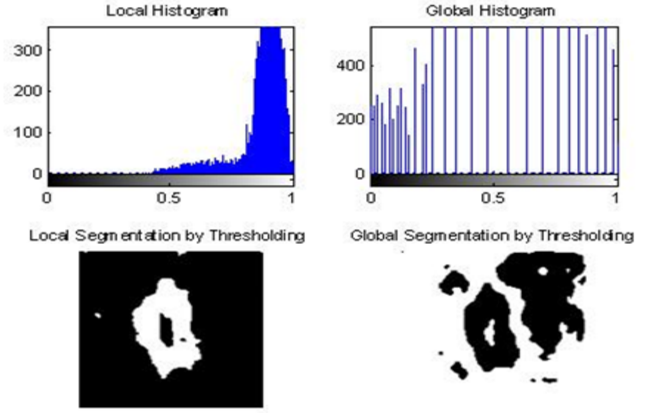

Figure 1. Result of segmentation by thresholding with GHE (bottom right) and LHE (bottom left), Top: shown histogram Local and Global results

A. Segmentation by Region of Interest (ROI)

Region of interest (ROI) is extracted by segmentation. The interesting features of melanoma are included within the border since most of the cancer cells are lump structures. The border structure provides vital information for accurate diagnosis. Many clinical features including asymmetry and border irregularity are calculated from the border. Threshold is an advanced method for segmentation to compute the intensity value from grey images. Fig. 2 shows the result of threshold segmentation where the white color represents the area of interest (ROI).

Figure 2. Segmentation, by Thresholding (ROI)

Figure 3. Segmentation by SRM

1) Thresholding

Thresholding is one of the segmentation methods that compute the intensity value from grey images. The image has to first be converted from RGB color space into grey scale. However, threshold segmentation is good as it separates the dark and light objects. The threshold values are calculated by histogram of RGB color band of the images. Fig. 4 shows an ideal histogram [1]. The skin and lesions should belong to the two peak values in the histogram since most of the color is belonging to the skin and the lesion.

The peak value of skin (Point S) should be higher than the lesion (Point M) because the skin has a lighter color than the lesion. Threshold low-point (Point V) is located at the lowest point between M and S and is determined by analyzing the pixel distribution of all intensity values. If the pixel in the image is higher than the threshold, then this pixel is set to be 1, or else 0. Fig. 2 shows the result of threshold segmentation where the white color represents the area of interest (ROI).

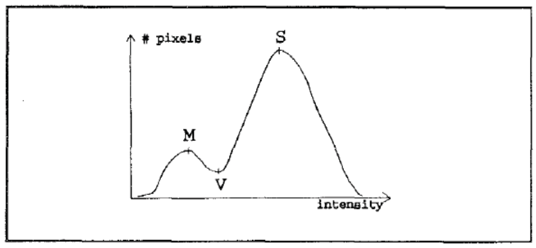

Figure 4. An ideal histogram

B. Segmentation by Region Growing (SRM)

Statistical region merging (SRM) algorithm is based on region growing and merging. The performance of SRM has a better segmentation result compared to other popular segmentation methods[2]. The theory of region merging starts at a seed point that is compared with its four neighbor points or pixels. The region is grown when the neighbors pixel share the same homogeneous properties. SRM usually works with a statistical test to decide the merging of regions. Fig. 3 shows the result of SRM segmentation where white color represents the area of interest. It is more accurate in segmentation and better than the threshold method. It includes more useful areas and does not put the outer region as part of the area of interest.

VI. FEATURE EXTRACTION

Feature extraction is the procedure that takes out the hidden properties or the raw data from the image that is further used in the classifier. In this section we look at modern methods of feature extraction namely, Wavelet and Curvelet transformations which are discussed and used in this paper. Thus approaches, such as discrete wavelet and discrete Curvelet, transforms the frequency information at different scales and locations are obtained [3].

A. Wavelet Transform

Wavelets are an extension Fourier analysis [4]. It is introduced with the advancement in multi-resolution transform research. The multi-resolution method is similar to image zooming process. When the image is zoomed out, we get a global view of the image. When the image is zoomed in, we get a detailed view of the image. Using the multi-resolution approach, we can get a complete picture of the image [5]. Wavelet analysis uses the terms approximations and details. Approximations are the high scale low frequency components while details are the low scale high frequency components. Approximations are what give the signal its identity. Wavelet decomposition can be a repeated process occurring over several levels. The original signal is decomposed into approximations feeding the next level of decomposition, creating a decomposition tree. This feature extraction was used in our previous work in[6] [7], the image energy is distributed according to the resolution. Each of the nodes represents one feature, which then can be used as an input for the classification stage. It was also mentioned in [6] [7], that the second level decomposition can generate 16 nodes or features. Two-dimensional wavelet packet returns the coefficients in 2 dimensional matrices. The features are calculated by their mean, maximum, minimum, median, standard deviation and variance. Therefore, 144 features for each image (16 nodes x 9 features) are produced to be input for classification system. This would increase the computation time without any improvement to the performance [6]. Therefore Principal Component Analysis (PCA) is suggested to be used before training process (by chosen PCA factor as 0.002, it reduce the 144 features into 60 features). Fig. 5 shows the original image and its transform (wavelet coefficients). This method allow useful cancer's feature to be extracted from the images without clinical knowledge.

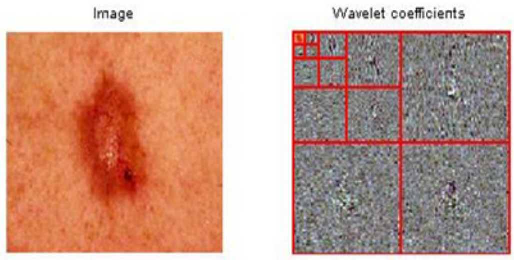

Figure 5. The image and its transform (wavelet coefficients)

The authors of [8] implemented image compression methods using various wavelet filter banks to improve image performance based on three distortion measures: Entropy of reconstructed image, energy retained (ER) and redundancy. Based on entropy and redundancy calculations it was found that Biorthogonal wavelets are superior as compared to orthogonal ones (wavelet packet) [9].

Unfortunately, wavelet ignores the geometric properties of objects with edges in higher dimensions and do not exploit the regularity of the edge curves [10] [11], which lead to unsatisfying results in the existing wavelet. To improve the method for curvy edges, the Curvelet transform is proposed a solution for this problem.

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In the last decade, there were a lot of activities in the development of new mathematical and computational tools based on multistate ideas permeated in fields of science and technology. A special member of this emerging family of multistate geometric transforms is the Curvelet transform [12] [13] [14] [15] [16], which was developed in the last few years in an attempt to overcome inherent limitations of traditional multistate representations such as wavelets. As explained in [6] [7], Curvelets are waveforms which are highly anisotropic at fine scales, with effective support obeying the parabolic principle (length ≈ width2). Just as for wavelets, there is both a continuous and a discrete curvelet transform. Fig. 6 Shown a single Curvelet and Fig. 7 displays representation of this joint localization.

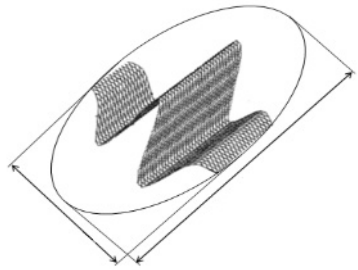


Figure 6. A single curvelet with width 2^{-j} and length $2^{-\frac{j}{2}}$

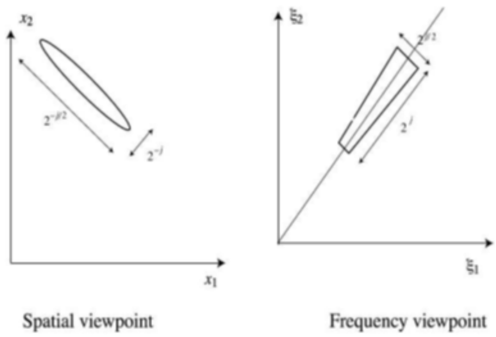


Figure 7. Schematic representation of the support of a curvelet in both space and frequency.

Conceptually, the Curvelet transform is a multi-scale non-standard pyramid with many directions and positions at each length scale, and at high scales, the Curvelet waveform becomes so fine that it looks like a needle shaped element (left images of Fig. 8 (b). Whereas, the Curvelet is non-directional at the coarsest scale (left image of Fig. 8(a)) [17]. With increase in the resolution level the Curvelet becomes finer and smaller in the spatial domain and shows more sensitivity to curved edges which enables it to effectively capture the curves in an image (Fig.9).

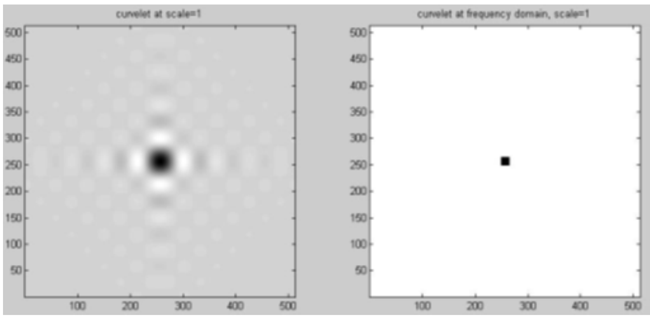
Curvelets have useful geometric features that set them apart from wavelets and the likes. If we combine the frequency responses of Curvelets at different scales and orientations, we get a rectangular frequency tiling that covers the whole image in the spectral domain as shown in Fig 8. Thus, the Curvelet spectra completely cover the frequency plane and there is no loss of spectral information like the Gabor filters.

To achieve higher level of efficiency, Curvelet transform is usually implemented in the frequency domain. The product is then inverse Fourier transformed to obtain the Curvelet coefficients. The process can be described as:

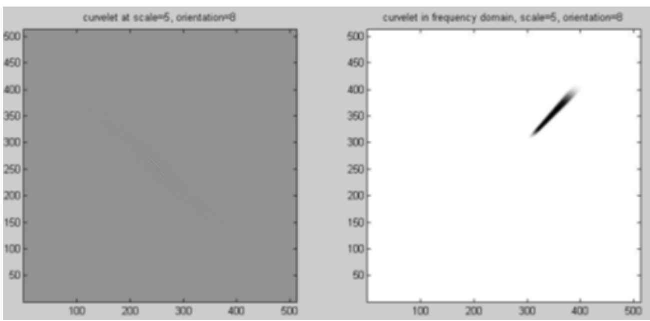
$$Curvelet\ transform = IFFT\,[FFT\,(Curvelet) \times FFT\,(Image)] \quad (3)$$

Equation (3) is based on the product from the multiplication is a wedge. The trapezoidal wedge in the spectral domain is not suitable for use with the inverse Fourier transform which is the next step in collecting the Curvelet coefficients using IFFT.

The wedge data cannot be accommodated directly into a rectangle of size 2 j ×2 j / 2. To overcome this problem, [15] as formulated a wedge wrapping procedure , where a parallelogram with sides 2 j and 2 j / 2 is chosen as a support to the wedge data (Figure 10).



(a)



(b)

Figure 8. Curvelets (absolute value) at different scales and a single direction are shown in the spatial domain (left) and the frequency domain (right).

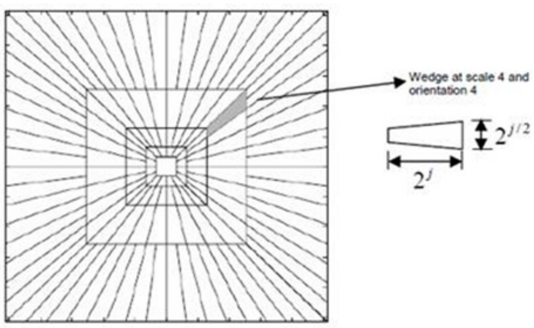


Figure 9. Rectangular frequency (basic digital) tiling of an image with 5 level curvelet

The wrapping is done by periodic tiling of the spectrum inside the wedge and then collecting the rectangular coefficient area in the center. The center rectangle of size 2 j × 2 j / 2 successfully collect all the information in that parallelogram (Fig. 10).

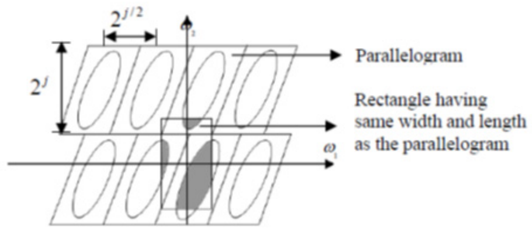


Figure 10. Wrapping wedge around the origin by periodic tiling of the wedge data. The angle θ is in the range (π / 4, 3π / 4).

The authors of [3] defined the product in above equation as a wedge. The trapezoidal wedge in the spectral domain is not suitable for use with the inverse Fourier transform which is the next step in collecting the Curvelet coefficients using IFFT. The authors in [16] have shown that wrapping based fast discrete Curvelet transform is much more efficient and provides better transform result than Ridgelet based Curvelet transform.

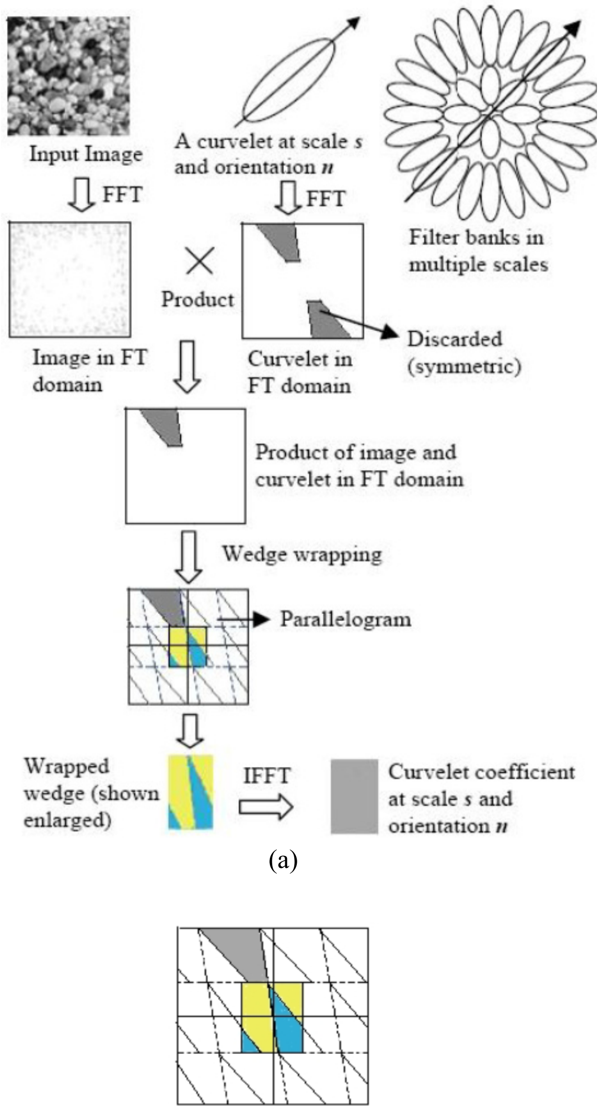
In the spatial domain, a Curvelet has an envelope strongly aligned along a specified `ridge' while in the frequency domain; it is supported near a box whose orientation is aligned with the co-direction of the ridge. (Note that these formulae allow us to analyze and synthesize arbitrary functions in L2(R2) as a superposition of Curvelets in a stable and concrete way [17]. This micro local behavior turns out to be key for understanding the properties of Curvelet-propagation [18].

The feature extraction of Curvelet has been done with MatLab software and the code consists of two parts. The first part computes the texture features from the Curvelet coefficients of each image in the database. The second part returns the Curvelet coefficients of a selected image to the first part.

Curvelet transform returns the set of Curvelet coefficients indexed by scale, orientation and location parameters. Calculate feature vector for each texture image in the database and insert those in order to another file. Then the database images are indexed in the feature database to be ready to calculate the mean and standard deviation of these coefficients. (Fig. 11)

Computation of Curvelet coefficients from image function is used to calculate the coefficients at the different scales and orientations of an image. Basically, we use the Curvelet coefficients in the cells for feature extraction. Fast Discrete Curvelet Transform via wedge wrapping is used to find the features.

For this wedge wrapping process, this approach of Curvelet transform is known as the ‘wrapping based Curvelet transform. The wrapping is illustrated in Fig. 11(b) and explained as follows: As shown in Fig. 11, in order to do IFFT on the FT wedge, the wedge has to be arranged as a rectangle. The idea is to replicate the wedge on a 2-D grid, so a rectangle in the center captures all the components a, b, and c of the wedge. We have to calculate the mean and standard deviation for the first half of the total cells at each scale. The test on



(a)

(b)

Figure 11. Fast discrete Curvelet transform to generate Curvelet coefficients.

melanoma image using Curvelet method is shown in Fig 12.

VII. Back-Propagation Neural Network (BNN)

Wide ranges of classifiers are available and each one of them has its strengths and weaknesses. Classifier performance depends on the characteristics of the data to be classified and there is no single classifier that works best on all given problems [6] [7].

An Artificial Neural Network (ANN) is a data processing system that simulates biological neural networks[19] [20]. It uses a great volume of simple and interconnected artificial neurons to simulate some properties of biological neural networks. Since neural network possesses high-speed calculation, memory, learning, blind signal separation, compression and filtering, it can solve many complex classification and prediction problems [21].

A neural network can perform the necessary transformation and clustering operations automatically and simultaneously. Neural networks are trained so that an input leads to a specified output. The training of the network is usually done

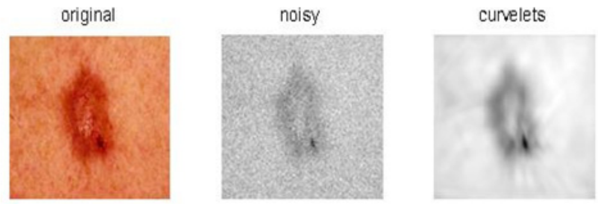


Figure 12. Curvelet denoising image that contains oriented texture and cartoon edges, (a) Original (b) Noisy, and (c) Curvelet.

through changes on the weights based on a set of input vectors. ANNs can model complex and nonlinear functions in many application areas including the pattern recognition, identification, classification, speech, vision, and control systems [20].

The Back-propagation Neural Network (BNN) is one of the most common neural network structures, as it is simple and effective. Back-propagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions [22]. The hidden and output layer nodes adjust the weights value depending on the error in classification. BNN has the benefit of prediction and classification but the processing speed is slower compared to other learning algorithms. In this work, BNN is utilized as a classifier as in our previous work in [6] [7] where it was proven that BNN has better performance and accuracy than other neural networks for this type of problem. An example of a multilayer feed-forward BNN is shown in fig 13.

A survey on artificial intelligence approaches for medical image classification has been presented in [23]. It addressed the applications of intelligent computing techniques for diagnostic sciences in biomedical image classification. It also mentioned some artificial intelligence methods that are used frequently together to solve the special problems of medicine. SVM and neural networks were focused on as they are being used in almost all imaging modalities of medical image classification. Similarly fuzzy C means and improvements to it were emphasized as important tools for segmentation of medical images. The survey also stated that hybrid approaches of genetic algorithms (GA) and Particle Swarm Optimization (PSO) are commonly used for feature extraction and feature selection [23].

In another study, Shreeja R. et al in [24], it is concluded that neuro - fuzzy method is a better technique for object recognition compared to neural networks. Their conclusion was based on the evaluation of a face recognition task using neural networks and neuro - fuzzy method. They used Curvelet transform for feature extraction where feature vectors were formed by extracting statistical quantities of curve coefficients.

VIII. Comparisons and Result

In our experiment, we used 60% of the total images for training, 20% for testing and 20% for validation. As well we used the weighted average in our measurements calculation. However the result achieved with highest accuracy is 86.57 % for Curvelet with BNN of two layers [20 10 neurons] where

Curvelet method has 28 % higher accuracy than wavelet in the classification test as shown in table 1 and fig. 14. The accuracy for neural network as a classifier is increased with the number of neuron in the hidden layer. The number of hidden layers could reduce the probability of over-fitting.

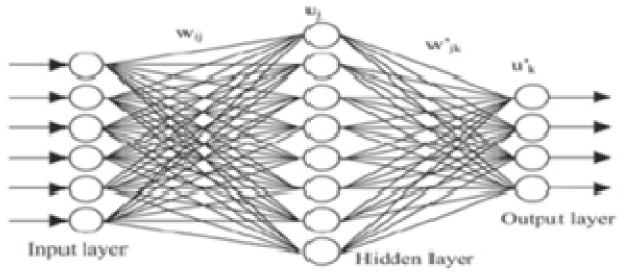


Figure 13. A Multilayer feed-forward network.

Table l. A comparison between wavelet and Curvelet features results.

Method	Neurons	Hidden	Training	Testing	Valid.
Wavelet	20 10	2	73.43	58.44	61.46
Curvelet	20 10	2	81.85	86.57	83.58

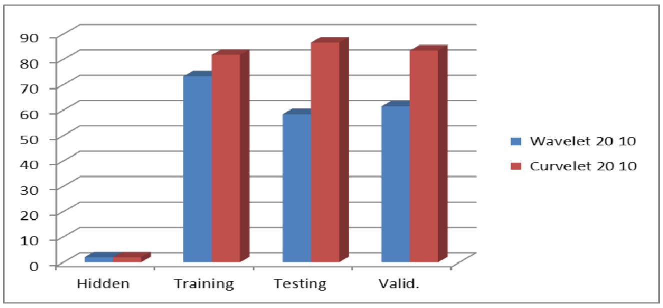


Figure 14. The bar graph diagram displays a comparison between wavelet and Curvelet features results.

Tables from 2 to 5 illustrated the result of using different layers with different numbers of neurons with both wavelet and curvelet.

For a comparison of the best accuracy results with the same numbers of hidden layer and neurons; Tables 3 and 5 shows the accuracy is 58.68 % for wavelet and 85.08 % for curvelet with one hidden layer [10 neurons], while is 86.57 % for curvelet and 58.44 % for wavelet with BNN of two hidden layers [20 10 neurons] and 57.66 for wavelet and 80.60 % for curvelet with three hidden layers [20 12 8 neurons].

IX. Conclusion

Building an image classification system for early skin cancer detection includes different stages: pre-processing and post-processing, segmentation, feature extraction and classification. The pre-processing resizes the image which improves the speed performance and removes the extra features such as the noise, fine hair and unwanted objects. Post-processing enhances the image quality and sharpens the outline of the cancer cell. On other hand, segmentation is used to find the region of interest by removing the healthy skins from the image and keeping the cancer cell whereas the feature extraction decomposes the useful features without prior clinical knowledge.

Table 2. Wavelet measurements.

No of Hidden Layers	No of Neurons	Training %	Testing %	Validation %
1	10	71.58	58.68	60.08
1	20	79.05	59.40	60.26
1	30	77.26	59.17	59.77
1	40	82.92	59.22	59.55
2	10 5	68.09	58.35	58.91
2	20 10	73.43	58.44	61.46
2	30 20	79.82	57.84	59.80
2	40 20	82.30	58.73	62.00
3	10 8 6	68.89	56.66	59.02
3	20 12 8	72.13	57.66	60.95
3	30 20 10	73.04	58.93	59.75
3	40 25 10	76.09	58.40	60.84

Table 3. Results of Wavelet accuracy with different number of layers.

No of Hidden Layers	No of Neurons	Testing %
1	10	58.68
2	20 10	58.44
3	20 12 8	57.66

Table 4. Curvelet measurements.

No of Hidden Layers	No of Neurons	Training %	Testing %	Validation %
1	10	85.3503	85.08	88.06
1	20	61.7834	44.78	52.24
1	30	73.8854	77.61	74.63
1	40	73.8806	75.56	74.44
2	10 5	48.4076	43.28	44.78
2	20 10	81.8471	86.57	83.58
2	30 20	59.8726	61.19	64.18
2	40 20	61.9403	68.89	67.78
3	10 8 6	63.0573	59.70	65.67
3	20 12 8	79.9363	80.60	80.60
3	30 20 10	72.9299	71.64	77.61
3	40 25 10	72.3881	75.56	65.56

Table 5. Results of curvelet accuracy with different number of layers.

No of Hidden Layers	No of Neurons	Testing %
1	10	85.08
2	20 10	86.57
3	20 12 8	80.60

The Curvelet properties and advantages have been discussed in detail. Principles of wrapping based discrete Curvelet transform have also been described. The classification results, which based on a database of mixed type of images, showed at table 1 as follows: 58.44 % for back-propagation neural network when using Wavelets and 86.57 % when using Curvelet [7]. Tables 2, 3, 4, and 5 showed different results recorded in different experiments as explained before.

This paper concludes that there are some possible factors for low classification results; one of the main factors that affect reaching high accuracy is the type of database used. This work has used a mix of images that were acquired from different sources mainly normal digital images and Dermoscopy images. While the proposed technique has tried to generalize the system working area, it has traded off the accuracy. A possible improvement and generalization can be achieved by dealing with the effect of large variation and overcoming it using larger databases.

X. Future work direction

As future direction for our work, we will use various wavelet families to improve image quality by analyzing the performance of orthogonal and bi-orthogonal wavelet filters for image compression through testing different variety of image sizes and resolutions. Alongside with that we will conduct more experiments on efficiently utilizing Curvelets for better representing curved edges.

We also intend to use a hybrid approach of genetic algorithms and Particle Swarm Optimization to improve feature extraction and feature selection.

Moreover, we are planning to use different and more advanced image classification techniques such as Support Vector Machines, Neuro Fuzzy algorithms to improve the classification accuracy.

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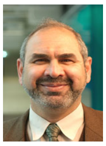

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