ISSN 2321 -9017
Volume 5, No.5, August - September 2017
International Journal of Bio-Medical Informatics and e-Health
Available Online at http://www.warse.org/IJBMIeH/static/pdf/file/ijbmieh01552017.pdf

Malignant Melanoma Diagnosis Using Intelligence Approaches

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ABSTRACT

Malignant melanoma is one of the major deadliest of skin cancers. Medical Informatics employs the computer technology for diagnostic such as Computer Aided Diagnosis (CAD). Many of researchers have developed CAD systems for melanoma diagnostic. The early diagnosis is leaded to reduce the melanoma-related deaths. This paper presents intelligence approaches namely, Artificial Neural Network (ANN), Adaptive-Network-based Fuzzy Inference System (ANFIS) and Support Vector Machine (SVM). The dermoscopy images are taken from Dermatology Information System (DermIS) and DermQuest, image enhancement is achieved by various pre-processing approaches. The extracted features are based on Discrete Wavelet Transform (DWT), and Principle Component Analysis (PCA) is used to take the eigenvalue as features. These features become the input to the various classification approaches such as ANN, ANFIS and SVM to classify the lesions as malignant or benign. The results show the rate of accuracy for ANFIS and SVM is 95.2%, while ANN gives higher rate of accuracy about 98.8%. Moreover; the comparative results are indicated that the proposed approaches have excellent accuracy than other approaches in this field of melanoma diagnosis.

Keywords— Computer Aided Diagnosis, Malignant melanoma, Medical Informatics.

1. INTRODUCTION

Malignant melanoma is a major threat in the developed world. The danger of melanoma is its ability to grow in any part in the body by lymphatic and blood vessels, and diagnose in its early stages is difficult [1]. Therefore, early stage diagnostic of benign and malignant melanoma is a crucial for reducing mortality and morbidity [2].

The dermoscopy images are imaging for melanoma diagnosis. The structure of a skin cannot be seen by the naked eye in clinical practice. Several clinical algorithms such as “image analysis”, “the ABCD rule”, “7-point checklist and “Menzies method” are currently used for diagnosing melanoma [3]. However, limitations of the clinical algorithms for diagnostics remain a crucial issue with dermatologists. Therefore, there is a need for a system to automatically diagnosis the melanoma from images.

Nowadays, the computer technology is employed by medical decision support, which helps the dermatologist to differentiate a benign from malignant melanoma. Such technology takes less time, and gives accurate diagnosis. Computer Aided Diagnosis (CAD) systems of melanoma are developed by many researchers, which overcome limitations of the clinical algorithms from the diagnostic process. Globally, CAD of melanoma involved four steps namely image acquisition, pre-processing, feature extraction, and classification. These steps can accelerate the diagnostic process; preprocessing step is necessary to improve the quality of images using different approaches such as image cropping, gradient operation, and morphological operation, scaling color space transformation, contrast enhancement and filters [4]. Also to remove all the problems like the presence of thin hair, low contrast, blood vessels that affect the images leading to less accuracy. Removing these problems makes the extraction of features more effective.

The characteristic of the melanoma lesion images are extracted in the feature extraction step, several approaches may be used for this purpose namely; texture features, color features, Discrete Wavelet Transform (DWT) features, Gray level Co-occurrence Matrix (GLCM) features, high-level intuitive features (HLIF) [5], and Local Binary Pattern (LBP) [6]; the most important features lead to accurate classification. Amelard (2015) [7], presented HLIFs approach for identifying the skin lesion. The results showed better classification accuracy. Almaraz et al. (2016) [8], developed a CAD system based on ABCD rule and textural features with SVM; the results showed accuracy about 75.1 %. The classification step is to recognize benign from malignant based on the extracted features; this step uses various classification approaches such as k-Nearest Neighbors (K-NN), Support Vector Machines (SVMs), Naïve Bayes (NB), Artificial Neural Networks (ANNs), adaptive-network-based fuzzy inference system (ANFIS) **,** Convolutional Neural Network (CNN) [6], Decision Tree, Logistic Model Tree (LMT) and Hidden Naive Bayes (HNB).

In this work, the enhancement is obtained by removal of illumination variations. The bilinear interpolation, morphological closing operations, an adaptive median filter and contrast are applied to improve images. DWT is used to extract the features from the images. Principle Component Analysis (PCA) is then applied to reduce complexity of data and calculate the variance of principle components for the proposed features. Various classification approaches like ANN, ANFIS and SVM are used to classify the extracted features into benign and malignant melanoma lesions.

The remaining parts of the paper are organized as follows: Section 2 presents related work to computer-aided systems for melanoma diagnosis. The proposed methodology is given in section 3. The results and discussion are explained in section 4. Conclusion and future work is given in section 5.

2. RELATED WORK

The previous researches have shown that CAD systems for melanoma are still a complex issue with respect to illumination variation. R. Amelard et al. [7] proposed multistage illumination modeling (MSIM); which used Markov chain Monte Carlo approach in this model to correct the illumination variation. M.E. Celebi et al. [9], presented accurate features with illumination variation, which used an iterative algorithm based on the luminance component of the color space Hue-Saturation-Value (HSV). The median filter is used to remove the hair from images [10], P. Schmid et al. [11] and H. Mirzaalian et al. [12] presented mathematical morphology approaches for hair removal. The artifacts from images are removed by using DullRazor approach, M. Messadi et al. [13] used dilation and erosion operation based on this approach. Adobe Photoshop detection is used by B. B. Salah et al. [14] manually to extract the correct position of the lesion. G.Tirupati et al. [15] presented a new approach for image contrast enhancement using DWT and Singular Value Decomposition (SVD). The performance of this approach is better than other contrast enhancement approaches, which gives high performance for segmentation and classification.

There are various types of approaches which were proposed to improve the accuracy of melanoma diagnosis, More specifically, in a recent study [14], proposed neuro-fuzzy system, color and area features are used in this system for discern different lesion types, the results are achieved between 97.4% (melanoma vs. benign) and 76.4% (Basal cell carcinoma vs. Squamous cell carcinoma); the extraction of features should be more accurate, which is the disadvantage of the system.

In another study [13], presented ABCD rule analysis and the ANFIS classifier to differentiate between malignant melanoma and benign lesions; the results are achieved accuracy of 92.3 %.

S. Choudhari et al.[16] , presented a CAD system based on GLCM with ANN, this system has got accuracy of 86.66%. An automated medical system is developed by M. Elgamal [17], which used DWT to extract the features, PCA is needed for reduction the dimensionality, and feed-forward neural network is used for classification, this system has got accuracy of 95%. On the other hand, our proposed system has accuracy about 98.8%.

S. M. Odeh [18], developed the optimization approach of the various features, which extracted by image processing, the results showed improvement in diagnosis. The drawback of this system is that it has low performance level due to the limited number of samples and long execution time.

I.G.Maglogiannis et al. [19], proposed an efficient methodology for the recognition of malignant melanoma, which is based on the SVM approach. The features are based on border and color, which allow the differentiation of malignant melanoma versus dysplastic nevus. The accuracy obtained by this approach is 94.1%.

X. Yuan et al. [20], developed an automated early melanoma detection, which based on a SVM-based texture classification algorithm. It showed 70% accuracy.

R. Garnavi et al. [3], presented a wavelet-based texture analysis approach for the recognition of malignant melanoma from benign. The proposed features are fed into SVM classifier. The accuracy obtained by this approach is 86.27%.

In this study, the disadvantages of the previous studies have been treated by extracting the necessary features. The extracted features are based on Discrete Wavelet Transform (DWT) and Principle Component Analysis (PCA) to take the eigenvalue as features that are used to develop our methodology. This proposed feature extraction approach is expected to enable dermatologist to achieve accurate diagnosis. In addition, various experiments were implemented in ANN using different values of the parameters to get the high levels of accuracy. When RBF kernel function is also used in SVM approach, it showed excellently achieving of accuracy.

3. PROPOSED METHODOLOGY

The structure of the proposed methodology for melanoma diagnosis is shown in Figure 1. The pre-processing is a necessary step to be carried out. Initially, the input images are improved by transformed into intensity color and then applied the morphological closing operations, an adaptive median filter and contrast adjustment. The output image becomes the input to the DWT, which decomposes the image and produces approximation coefficients. PCA is applied to produce low dimension data; then, the system classifies the image using various classification approaches namely ANN, ANFIS and SVM. Finally, the performance is compared based on sensitivity, specificity, and accuracy. In the following lines the implementation details for each step of the proposed methodology diagnosis are discussed.

3.1 Data Sets

For this study, the dermoscopy images are sampled from Dermatology Information System (DermIS) and DermQuest [21]. The data-set contains a total of 204 images out of which 119 are malignant and 87 are benign. The images are acquired in varying environmental conditions. Figure 2, presents sample images of skin lesions for this dataset. These images are divided into two datasets, 60% as a learning set and 40% as the test set. All images are resized to be [512*512] pixel prior to feature extraction. This system is implemented in MATLAB software version 2016.

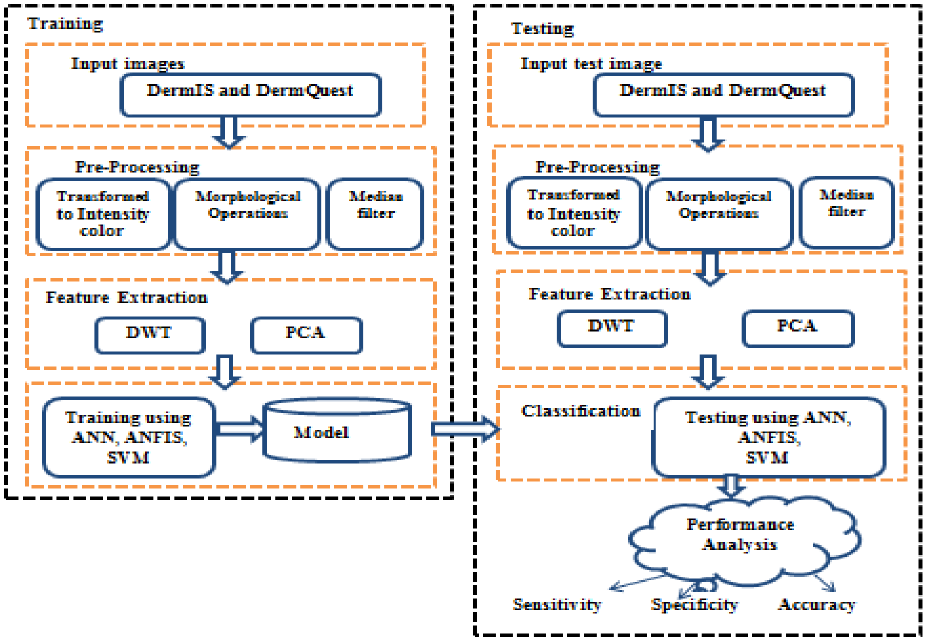
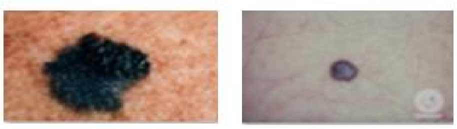


Figure 1: Proposed Methodology



(a) (b)

Figure 2: Dermoscopy image examples: (a) melanoma image; (b) benign image

3.2 Image Pre-Processing

There are certain impacts on digital images cause errors in the classification like the thin hair, illumination variation effects and air bubbles [22]. Therefore the pre-processing step is very important for noise removal and improved quality of the images. The pre-processing performed here is shown in Figure 3; it contains four processes as follows:

1- The original images are transformed from RGB color space to intensity color space.
2- Bilinear interpolation and morphological closing operations are used for hair removal.
3- The images are filtered using an adaptive median filter, this technique removes the noise produced during image acquisition; also, to eliminate the hairs [23].
4- The image is enhanced by contrast adjustment; it is increased by mapping the pixel values of the image to new values using gamma correction of about 0.2.

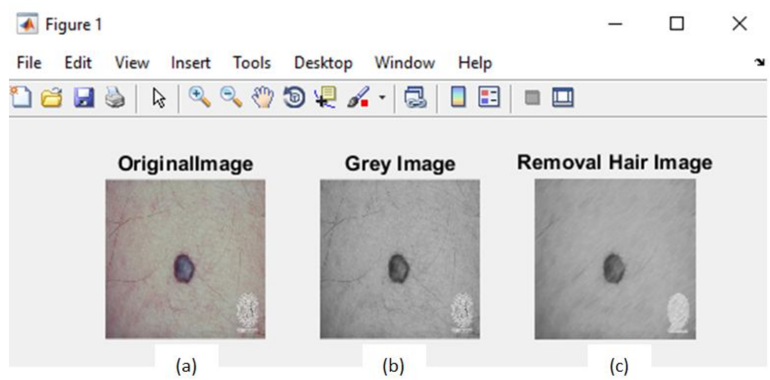


Figure 3: The processes of pre-processing a) original image, b) gray image, C) image after hair removal

3.3 Feature Extraction

Feature extraction is used to extracts the unique features from the images of skin lesion. The efficiency of the diagnostic is improved by using the most important features which accurately characterize a lesion [24]. In this section, DWT and PCA approaches are discussed. First, the images are transformed using DWT dividing it into approximate and three detailed images which show the basic information, vertical, horizontal and diagonal details, respectively. Second, PCA is applied on the features that are extracted from the transformed data, which reduces the complexity of data and produces a more accurate classifier.

3.3.1 Discrete Wavelet Transform (DWT)

DWT has been widely used in image processing applications, it is an efficient approach for representation and analysis of images, that overcome the limits of Fourier transforms, localized in both frequency and time domain; this is an advantage over the Fourier transforms [1]. It uses the multi-resolution approach to get a global view of the image. It divides an image into 4 sub-bands with low–low (LL), low–high (LH), high–low (HL), and high–high (HH) components at each scale, which correspond to approximation, horizontal, vertical and diagonal, respectively. The LL sub-band is the feeding for the next 2D DWT; the procedure can be repeated over several levels of decomposition, building a decomposition tree. The LL sub-band is the approximation component of the image giving identity of the image; the LH, HL, and HH sub-bands represent the detailed components of the image [4]. R. Garnavi et al. [3], utilized wavelet transform on different color channels of skin images. Various statistical measures have been employed on wavelet coefficients; the accuracy obtained by this approach is 88.24%. N.Fassihi et al. [25], utilized features are based on the variance and mean for the wavelet coefficients of images, it has got accuracy of 90%.

In this research, the first level decomposition via Debauchees-1 wavelets function is utilized to extract features, it is a very popular function used by many researches. Figure 4, shows the decomposed wavelet. At the first level of decomposition, the original image is divided into approximation coefficients, horizontal coefficients, vertical coefficients and diagonal coefficients respectively. The approximate image is used instead of the original one. Finally, PCA is utilized on the approximate image.

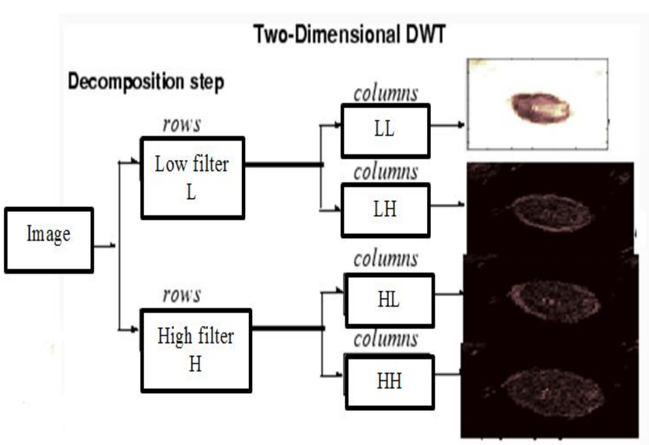


Figure 4: The wavelet decomposition of image

3.3.2 Principle Component Analysis (PCA)

PCA is a successful feature reduction approach that is used in prediction, redundancy removal, feature extraction, data compression, etc. It is targeting to reduce high dimensionality of the data. It is also used in case of strong correlation among the observed data. M. Elgamal et al. [17], proposed an automated medical system, DWT is applied on the images, and then PCA is utilized on feature vectors to reduce the dimensionality of those vectors. It determines the lower-dimensional representation of the data like the variance [22]. So, the aim of using PCA in our methodology is to reduce the dimensionality of the wavelet coefficients. Principal component coefficients are produced as matrix, the rows of this matrix indicate the total images and each column contains coefficients of principal components for each image in the order of descending variance. The Principal component variances are taken as features that represent the eigenvalue of the covariance matrix (Figure 5). This leads to have a few feature vectors; that causing to produce a more accurate classifier.

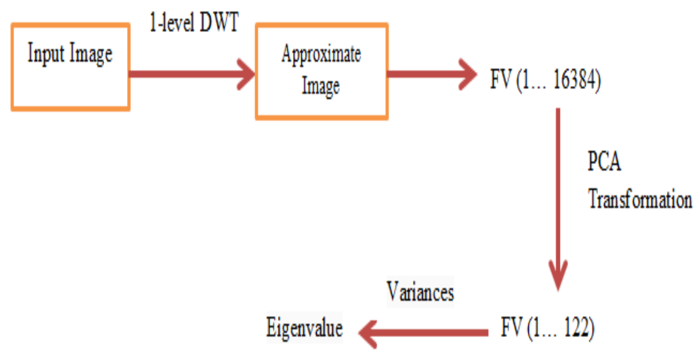


Figure 5: Feature extraction of image using DWT and PCA

3.4 Classification

The classification refers to discern the extracted features from images into malignant melanoma and benign [26].
An artificial neural network (ANN) is a computational model; it has the most effective approaches for pattern recognition. Neuro-fuzzy systems are subfield of artificial intelligence, it is the combination of ANN with fuzzy systems, includes the advantages of both approaches. In addition SVM classifiers have been widely used in medical image diagnostic; a detail of these approaches are described as follows.

3.4.1 Artificial Neural Network (ANN)

ANN is the effective approach for medical diagnostic, it consists of three layers namely the input layer, the hidden layer, and the output layer [8]. In this proposed system, the Back propagation approach is utilized in ANN classifier.
First, the weights are initialized randomly; it trains a set of input/output pairs, according to the initial weights an activation function hyperbolic tangent sigmoid transfer and linear transfer are used, It adjusts the weights during each epoch to minimize the mean squared error between the actual

output and the desired output. An error is produced when both are not identical. This error is propagated backwards and weights are updated, when the difference between the required output and the actual output are minimized the training is stopped [4]. The ANN Parameters' information used for training is summarized as follow.

Number of input layer units: 1

Number of hidden layer is varied between 10 and 30

Number of epoch is varied between 500 and 2500

Number of output layer units: 1

Momentum constant: 0.9

Learning rate: 0.05

Performance goal: 0.006

Training function: Bayesian regularization

Activation function for input layer: hyperbolic tangent sigmoid transfer.

Activation function for output layer: Linear transfer.

3.4.2 Adaptive-Network-based Fuzzy Inference System (ANFIS)

ANFIS is an adaptive network of artificial intelligence approach; it allows the usage of the best characteristics of ANN and fuzzy logic. It includes the advantages of both approaches with the target of having fuzzy systems using a back propagation algorithm try to minimize mean square error. This model consists of a set of if–then rules and membership functions to represent the input–output in the fuzzy inference system [27].

The ANFIS consists of five layers, namely fuzzification layer, product layer, normalizes the membership functions layer, de-fuzzy layer and total output layer [28]. For simplicity to illustrate the proceeding of the ANFIS, we consider that adaptive system has two inputs x, y and one output f, and a first order Sugeno fuzzy inference system, hence, the rule base containing two if–then rules:

Rule 1: if x is A1 and y is B1 then f = p1x + q1y + r1.

Rule 2: if x is A2 and y is B2 then f = p2x + q2y + r2.

Where p1, p2, q1, q2, r1 and r2 are linear parameters and A1, A2, B1, B2 are nonlinear parameters, which A1 and B1 are the membership functions of ANFIS system [13].

S. M. Odeh [18], presented a diagnosis system based on ANFIS, it showed good performance accuracy in the skin lesions diagnostic. B. Salah et al. [14], developed ANFIS system, it has got accuracy 91.26%. Our proposed system has got accuracy about 95.18%.

In this study the ANFIS approach is utilized for melanoma diagnostic, we use a Sugeno-type fuzzy inference system. The

gradient descent and Back propagation algorithms are used to adjust the parameters of membership functions (fuzzy sets) and the weights of defuzzification (neural networks) for fuzzy neural networks. The obtained information of ANFIS is summarized as follow.

ANFIS info:

Number of nodes: 12

Number of linear parameters: 4

Number of nonlinear parameters: 6

Total number of parameters: 10

Number of training data pairs: 121

Number of testing data pairs: 83

Number of fuzzy rules: 2

The training was run for 10 iterations. The network performance is evaluated on the testing set, the root-mean square errors (RMSE) is calculated after each iteration [18]. The optimal number of iterations obtained is 10 epochs by the time RMSE, its minimum value is 0.009000 after epoch 10. Finally, the error is converted from RMSE to percentage form. The eigenvalue is provided to the proposed ANFIS classifier in order to recognize between malignant melanoma and benign as shown in Figure 6.

3.4.3 Support Vector Machine (SVM)

SVM is a supervised learning method implemented for classification and regression [3]. Data analysis applied in the field of cancer prediction/prognosis is based on statistical learning theory. This method is used for classifying linear as well as non-linear data. Non-linear mapping technique is used to transform the original training data into a higher dimension. Aim of the SVM algorithm is to produce hyper-plane to split the two types of data by maximizing the margin separating the two classes and the same time ensuring minimization of the expected classification error to avoid misclassification of the test sample [20].

The resulting classifier achieves considerable generalizability and can therefore be used for the reliable classification of new samples. Figure 7, shows principle of SVM that the line w.x-b=0 is a marginal line. The lines w.x - b = 1 , w.x – b = -1 are lines of both sides of the margin. The hyper plane is constructed by these lines that separate the given samples; the samples that lie on the edges of the hyper plane are called support vectors [29].

SVMs only implement classifying hyper planes; successful building of non-linear decision planes is reached through effective mapping of the data into higher-dimensional space using kernel functions. Polynomials and Gaussian radial basis functions (RBFs) are the common kernel functions.

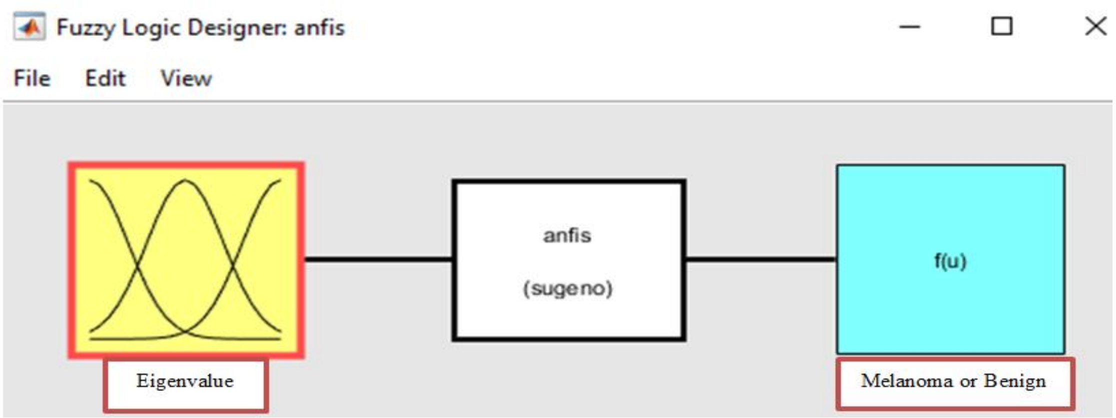


Figure 6: ANFIS System for melanoma diagnostic

Importance of misclassifications on the training set depends on specifying a cost factor C for any kernel function [19].
To achieve better generalized performance on new data, empirical error should be minimized and complexity of the kernel functions has to be controlled.
Among all kernel functions, the Radial Basis Function (RBF) is the best as it is computationally more stable and has fewer hyper parameters. So we train an SVM classifier using RBF Kernel.

It could have output errors known as (misclassification); the system may diagnose a normal lesion as malignant melanoma, or diagnose the malignant melanoma as normal. Performance of the classification is done according to sensitivity, specificity, and accuracy. Diagnosis result was given in terms of true positive (TP), false positive (FP), true negative (TN) and false negative (FN) [9]. They are calculated through the equations (1, 2 and 3) shown below.

$$\textbf{Sensitivity (SE)} = \frac{TP}{TP+FN} * 100\,\% \qquad (1)$$

$$\textbf{Specificity (SP)} = \frac{TN}{TN+FP} * 100\,\% \qquad (2)$$

$$\textbf{Acuuracy (AC)} = \frac{(Tp+TN)}{(TP+TN+FP+FN)} * 100\,\% \qquad (3)$$

Where, TP refers to the cancerous image that is classified by the system as cancerous. TN refers to the non-cancerous image that is classified by the system as non-cancerous. FP refers to the image that is classified by the system as cancerous image, but in fact it is not cancerous. FN refers to the image that is classified by the system as noncancerous image, but in fact it is cancerous.

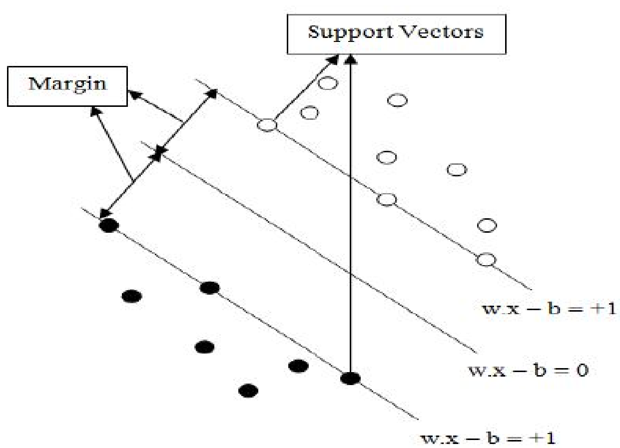


Figure 7: Principle of SVM [29]

4. RESULTS AND DISCUSSION

Several experiments are carried out to evaluate the efficiency of melanoma diagnosis system. The proposed work compared three classification approaches ANN, ANFIS and SVM with the feature extraction method DWT for melanoma diagnostic. The dataset contains 119 images belonging to malignant melanomas and 87 images belonging to nevi. DWT is used for feature extraction and PCA for dimension reduction. Feature vector is calculated for each input image and these inputs are fed to the approaches for classification. The execution is done in MATLAB software. The proposed approaches trained with 60% and tested with 40% of the dataset. Then, the output of sensitivity, specificity, and accuracy are computed to evaluate the performance as discussed in the above.

Table 1, shows the result of using different values of neurons in the hidden layer of the wavelet with ANN. For training function, it is interesting to note that Bayesian regularization performs better than Levenberg-Marquardt back propagation. It displays best accuracy of 96.4% is associated with 30 neurons in the hidden layer and 500 epochs. Tables 2, shows the result of using different numbers of epochs in wavelet transformation with ANN; for Bayesian regularization training function, it gives best accuracy of 98.8% resulted when using hidden layer of 30 neurons and 2500 epochs. The Levenberg-Marquardt back propagation provides 98.8% accuracy using hidden layer of 30 neurons and 1000 epochs.

The *receiver operating characteristic (ROC)* is shown in Figure 8; it checks the quality of ANN classifier. It displays the curves of output classes; the class 2 is better classification than class1 because its curve closes to the left and top edges of the plot.

Table 3 and Table 4; illustrate the outcome of different approaches on melanoma images. Performance is based on output results calculation.

Table 3, shows the computed True Positive, True Negative, False Positive, and False Negative values respectively on the test data. The dataset consists of 83 images; ANFIS and SVM classifiers erroneously classified 4 non-cancerous images as cancerous, whereas ANN erroneously classified 1 cancerous image as non- cancerous.

Table 4, shows the sensitivity, specificity and accuracy of the feature extraction approaches on the testing data. According to the results, ANN is more effective for detection of melanoma from benign. It displayed the best performance among the classification approaches with an accuracy of %98.8. Figure 9 shows the results of various approaches in terms of sensitivity, specificity, and accuracy.

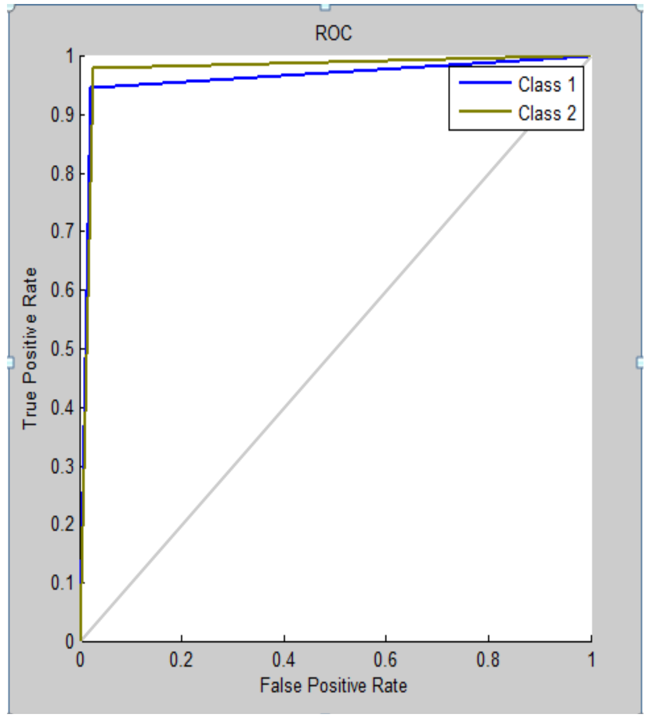


Figure 8: ROC for each output class

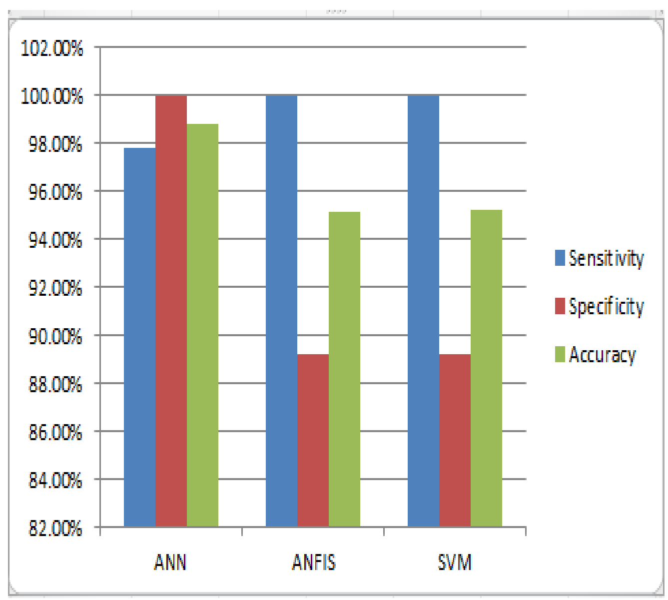


Figure 9: The bar graph diagram displays a comparison between ANN, ANFIS and SVM results

Table1: Results of Wavelet Accuracy with Different Number of Hidden Neurons

Approach	No of hidden neurons	No of epoch	Training function	Training	Testing	Training function	Training	Testing
DWT+PCA+ANN	10	500	Bayesian regularization	100%	77.1%	Levenberg-Marquardt back propagation	100%	77.1%
	15			75.2%	84.3%		100%	77.1%
	20			79.3%	91.6. %		79.3%	92.8%
	25			81%	95.2%		78.5%	87.95%
	30			83.5%	96.4%		79.3%	91.6%

Table2: Results of Wavelet Accuracy with Different Number of Epochs

Approach	No of hidden neurons	No of epoch	Training function	Training	Testing	Training function	Training	Testing
DWT+PCA+ ANN	30	500	Bayesian regularizati on	83.5%	96.4%	Levenberg-Marquardt back propagation	79.3%	91.6%
		1000		81.1%	94.0%		84.3%	98.8%
		1500		81.8%	94.0%		76.9%	85.5%
		2000		83.5%	97.6%		76.9%	85.5%
		2500		84.3%	98.8%		79.3%	92.8%

Table 3: PERFORMANCE of the Used Classifiers

Approaches	Test Set	True + ve	True - ve	False + ve	False - ve
DWT+PCA+ANN	83	45	37	0	1
DWT+PCA+ANFIS	83	46	33	4	0
DWT+PCA+SVM	83	46	33	4	0

Table 4: Comparison between ANN, ANFIS and SVM Results

Approaches	Sensitivity	Specificity	Accuracy
DWT+PCA+ANN	97.8%	100%	98.8%
DWT+PCA+ANFIS	100%	89.19%	95.2%
DWT+PCA+SVM	100%	89.19%	95.2%

Table 5: Comparative Results of Different Studies

Author	Datasets	Approaches	Accuracy
Proposed approaches	DIS and DermQuest	DWT+PCA+ANN DWT+PCA+ANFIS DWT+PCA+SVM	98.8% 95.2% 95.2%
M. A. Arasi et al. (2016) [30]	DIS	DWT+PCA+SVM DWT+PCA+K_NN DWT+PCA+ANN	86.67% 90% 96.7%
Karabulut et al. (2016) [6]	DIS and DermQuest	LBP+ SVM LBP+ CNN	71.4 % 71.4%
J.A. Almaraz et al. (2016) [8]	DIS and DermQuest	(ABCD Rule And Textural Features) + SVM	75.1 %
M. Messadi et al. (2014) [13]	Department of Dermatology, Health Waikato New Zealand	ABCD+ ANN ABCD+ ANFIS	87.32% 92.31%
J.A. Jaleel et al. (2013) [4]	NA	DWT+ANN	84%
R.Amelard et al. [5] (2012)	DIS and DermQuest	HLIF+SVM	87.38%
N.Fassihi et al. (2011) [25]	NA	DWT+ANN	90%
B.Salah et al. (2011) [14]	NA	Color and area features +ANN Color and area features +ANFIS	90.67% 91.26%

NA: Not Available

Table 5, shows the results of different classification approaches for various studies. (DermIS) and DermQuest datasets are the common dataset for our study and other studies [5], [6], [8], [30]. The results show that HLIF combined with SVM gives better feature extraction results compared to LBP combined with SVM approach in [5] and [6].

DWT with ANN is better in diagnosing malignant melanoma giving the highest accuracy [4], [25]. On the other hand, the ABCD method gives best results with ANN and ANFIS approaches than SVM [8], [13]. Our proposed methodology is an extension of previous work [30] that uses the combination of two datasets (DermIS) and DermQuest, also utilized the best feature extraction DWT and hybrid classification approach to get the highest accuracy in discrimination among benign and malignant melanoma lesions.

5. CONCLUSIONS AND FUTURE WORK

In this paper, an automated diagnosis system is introduced for melanoma diagnostic, it showed excellent performance compared to other systems that use the same datasets. The proposed system is based on 204 images in a dataset 119 of which are malignant and 87 are benign. Image processing approaches are utilized for improving these images, and then DWT is applied on the images to get unique features, after that we need to reduce the dimensionality of this data through PCA. The variance of Principal components (eigenvalue) is obtained as the feature for each image. Afterwards, these features are used for classification. The classification approaches ANN, ANFIS, and SVM are employed and compared the results based on sensitivity, specificity and accuracy.

The results of testing by using ANFIS and SVM gave the same accuracy 95.2 %, while using ANN gave the best results. On the other hand, by varying the parameters of ANN experiments, the accuracy is improved to 98.8%. We concluded that the proposed methodology got an excellent accuracy and it is very useful for melanoma diagnosis than other approaches.

In future, we will use a hybrid features including GLCM, color and DWT. Also, we plan to improve the classification approaches, and testing on non dermoscopy images. In addition, the results can be compared with this work.

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