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The Study of Recognition Methods Based on Wavelet Transform for Melanoma Detection

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Authors' contributions

This work was carried out in collaboration between both authors. Author MA performed the experiments and their analysis, managed the dataset, managed the analyses of the study, managed the literature searches and wrote the first draft of the manuscript. Author KD managed the algorithm, designed the study and the experiments, contributed in the analyses of the study and supervised on the first draft of the manuscript. Both authors read and approved the final manuscript.

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ABSTRACT

Skin cancer is one of the most cancers occurring in the world. Malignant melanoma is the most skin cancer type causing death around the world. Melanoma could be treated 100% if they are detected at earlier stages. In this paper, various melanoma detection systems were reviewed according to the year of publishing. All reviewed papers were based on feature extraction methods using wavelet transform (WT) in its two versions: Discrete wavelet transform (DWT), and wavelet packet transform (WPT) for melanoma recognition. Our methodology that was based on the WPT feature extraction and probabilistic neural network (PNN) was used for comparison. The ISIC database was used for differentiating between malignant (1110 images) and benign (1110 image) tumors. A (75% training /25% testing) verification system was applied. Many experiments were conducted using different parameters for each experiment. The support vector machine classifier (SVM) was the most common classifier combined with various types of wavelet features that have appeared in many kinds of literature during the last two decades, which achieved relatively the best accuracy ranged between [76% - 98.29%]. In this paper, our combination method of the WPT and entropy was proposed and evaluated. Several experiments were conducted for testing. A

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comparison manner was used for discussion of the investigation. The proposed method was an excellent detection method for melanoma regarding the complexity, where no preprocessing stage was conducted.

Keywords: Skin cancer; melanoma; wavelet transform; probabilistic neural network.

1. INTRODUCTION

One of the most death-causing cancer diseases is skin cancer, particularly if not detected at earlier stages. According to the world health organization (WHO), there are about 132,000 malignant melanoma cases and 66,000 death cases of malignant melanoma in the world annually [1]. Skin is the largest organ in the human body, which consists of three main layers: Dermis, epidermis, and hypodermis. The skin has an important role in the body protecting against outer affected factors such as bacteria, temperature changes, and exposure to ultraviolet radiation (UVR) [2]. UVR is one of the most common reasons that lead to skin cancer. Those UVR rays are powerful enough to reach your epidermis layer in the skin and damage the DNA. That's what leads ultimately to skin cancer. The delay from the time of damage and when the cancer shows up can be many years.

Dermatologists are facing crucial issues in verifying of the malignant melanoma by using their vision or dermoscopy. The diagnosis by using dermoscopy or eyes are not accurate and takes time to give the final diagnosis result. Early melanoma detection will increase the probability of treating malignant melanoma by up to 90%. In the year 1994, Franz Nachbaur [3] proposed a clinical of dermoscopy method for melanoma detection known as ABCD rule (Asymmetry, Border Irregularity, Color variance, and the Diameter size). This rule was assessed by a scoring equation for each evaluation method. The ABCD rule works only for melanocytic lesions.

Recently computer systems have come to help dermatologists in melanoma detection. Most of the detection systems consist of five main steps: image acquisition, preprocessing, feature extraction, classification, and finally evaluation. There are many published papers which focus mainly on the classification systems to differentiate between malignant melanoma and benign lesions. In this work, we will focus on decent research journals such as IEEE, Springer, Elsevier, and MDPI journals. This paper is designed to study the detection systems of melanoma that depend on one of these feature extraction methods: Discrete wavelet transforms (DWT), wavelet packet transforms (WPT) and Gabor wavelet Transform (GWT). Malignant melanoma is difficult to be recognized depending only on vision. There are three main aims in this study: Firstly, to study the previous methods (papers) that used WT and DWT. Second, to differentiating between malignant melanoma and benign nevus based on feature extraction using WPT and wavelet entropy (WE) algorithm. Finally, to determining the best parameter results with some experiments.

The paper is divided into different sections as follows: Introduction, Literature review, Experiments, Results and Discussion and Conclusions.

2. LITERATURE REVIEWING

In the early 1990s: WT has been used for image processing [4]. The wavelet transform has been applied to the melanoma detection systems since 2002. In the early 2000 century, scientists began to apply the wavelet in melanoma detection. Around 30 researching papers are reviewed in the following context then they are summarized in Table 1. In the following literature, we will discuss the common and different methods for each five years from 2000 to 2020.

From 2000 – 2005: There was only one research paper designed to classify melanoma by an adaptive wavelet-based tree structure classification method. At that time, the limitation of the dataset, which consists of 10 melanoma images/20 nevus images [5], had affected the spreading of the research. In the paper [5], the wavelet function type Daubechies-3 (db3) was used with four levels of decomposition and the mean energy ratios and different threshold values were selected to obtain high classification results. The obtained results by calculating the sensitivity and specificity were presented for detection.

From 2006 – 2010: Eight papers were published in this period are selected in this research. The testing datasets used in these papers were created from a hospital or colleges. A preprocessing technique has been implemented for image enhancement like median filer [8,10]. Some of these papers used statistical parameters combined with WT were used in [10,13]. DWT was utilized in [12] with a set of features. The principal component analysis was used with WT in [8]. The evaluation results of these methods were relatively high.

From 2011- 2015: There are six published papers in this period. Most of these research papers used the preprocessing stage to remove the artifacts by applying the median filter and wiener filter. Segmentation also was proposed to remove the background from the lesion. Two of these papers had the same dataset [14,19]. WPT was applied in [14] and [18]. The feature extraction [19] was WT. The PCA and curvelet Transform (CT) is also combined as in references [14,19]. In [15-17], the WT was used with statistical parameters. The DWT was used in [15] with the PNN classification method, which achieved a highly accurate result. SVM also was used for classification in [16,17,19]. Based on that information, we can notice that the research here is continuous to the last period in terms of methods used.

From 2016 – 2020: There are twelve published articles in this period. And there is a common dataset used in three articles [23,24,29] from DermQuest and two papers used PH2 dataset [27,31]. In the preprocessing stage, most of these papers applied different image sizes of the same implemented dataset. Some papers applied the median filter to remove unwanted objects such as air bubbles as in references [20], [23,24]. Amir Reza suggested the hair removal from the images in [22], Spatarshi at [26], Uzma [27] and Akhiyar [31]. Each paper used different or similar classification methods to calculate the output results. One type of WT was used in each research combined with the color feature as in [20,21]. The texture features are used in [24-26], [28,31]. The statistical parameters were implemented in [26]. Table 1 summarized all reviewed methods published from 2002 until 2020. Fig. 1 shows the block diagram of the reviewed papers.

3. RESULTS AND DISCUSSION

Experiment 1

In this experiment, an automatic detection algorithm is proposed. The algorithm was created using MATLAB software. Many procedures are conducted over the data that was collected from the ISIC archive [6]. The data consists of 1110 malignant melanoma/ 1110 benign nevus. A (75% training/25% testing) system is performed for all experiments. All images were resized to (80x250) pixels. The feature extraction is implemented by WPT using “wpdec” MATLAB function combined with entropy measures calculated using the “WENTROPY” MATLAB function [7]. The classification was conducted by PNN. Finally, the results are reported and achieved. Our system is conducted by the same procedure summarized in Fig. 2. The mother of wavelet packet transform (WPT) could be defined mathematically as the following equation:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-b}{a}\right),\ a,b \in R, a \neq 0$$

Where: a representing the scaling, b: the shifting. ψ: the mother wavelet. R: real numbers.

The wavelet transform could be representing as the following equation:

$$wt(a,b) = < x, \psi_{a,b} > = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right)dt$$

Where: X(t) the input images. ψ^{*} is conjugate version of the mother wavelet function, x representing the input data. a and b may be translated or dilated [8].

Experiment 1: Determining the optimal solution of parameters P1 and P2

In this experiment, we set the WPT at level 5 to test the algorithm for different thirteen wavelet functions (db1, db5, db10, sym1, sym5, sym10, bior1.5, bior2.6, bior3.5, bior3.9, coif1, coif3, coif5). These wavelet functions are selected randomly. All the trials are conducted with each entropy of Threshold, Sure, Norm, separately, and tested.

First: Threshold entropy

Firstly, the values of P1 and P2 are selected randomly with a range between (0-1000) as follows: (0, 5, 10, 15, 20, 30, 50, 100, 150, 200, 250, 300, 350, 400, 450, 500, 550, 600, 650, 700, 750, 800, 850, 900, 950, 1000). There are 676 trails for each wavelet type, the total of 8788 trails are conducted with loops. These results are collected and reported to calculate the average recognition rate for all thirteen wavelets these results were reported and achieved. Threshold entropy is defined as the following:

$E_1(S_i) = 1\ if\ |S_i| > \varepsilon\ and\ 0\ elsewhere, so\ E_4(s) = \#\{i\ such\ that\ |S_i| > \varepsilon\}$ Is the number of instants when the signal is greater than a threshold ε. (1)

Table 1. Summary of reviewing papers of a melanoma detection system based on WT, WPT, DWT, GWT. NA: not available. Similar dataset recognized in the following symbols (, ***, ****, *****)**

Author, year	Preprocessing and segmentation	Dataset information	Feature extraction	Classifier	Results and accuracy
Sachin, 2002 [5]	NA	10 melanoma/ 20 Benign	WT	Frequency information	Sensitivity (TPF) 90% Specificity (FPF) 10%
Grzegorz, 2007 [6]	NA	39 images from Collegium Medicum of the Jagiellonian University**	WT With 231 features	NN-MLP, SVM, AQ21	AUC=97.4%
Andy Chiem, 2007 [9]	Median filter Contrast enhancement	University of Iowa	WPT, PCA	BPNN	95%
				SVM	85%
Grzegorz, 2008 [10]	NA	39 images from Collegium Medicum of the Jagiellonian University**	WT With 231 features	TF, ATF SVM, MLP	TPF=94.7% FPF=5%.
Kathy, 2009 [11]	NA	25 Benign nevi / 5 melanoma	Harmonic – WT	NN	93.3%
Ho Tak Lau, 2009 [12]	Median filter	448 images from Sydney hospital***	WT + statistical parameters	BPNN	89.9%
				AANN	80.8%
Grzegorz, 2010 [13]	Scaling images to 800x600, remove the background	dermoscopic images 78 melanomas 80 nevi	Features A	TF	%93
			Features B sets based on WT	ATF	%100
Ning Situ, 2010 [14]	Histogram representation	100 images 70 benign/30 melanoma 80% of training 20%testing	a set of features including DWT	Multiple Kernel Learning (MKL) Based on SVM	Sensitivity: 83% Specificity: 80.93 %
Rahil, 2010 [15]	Cropping manually	205 dermoscopy images are used 103 training/102 testing	WT + Eight statistical measures	SVM	86.27%
				RF	86.27%
				LMT	88.24%
				HNB	86.27%

Author, year	**Preprocessing and segmentation**	**Dataset information**	**Feature extraction**	**Classifier**	**Results and accuracy**
Md. Khalad, 2011 [16]	Wiener filter, median filter, segmentation	448 images from Sydney hospital***	144 features with 2D-WPT + PCA and CT.	BPNN	75.6% with CT 51.1% with WT
Yogendra, 2012 [17]	Edge detection by contour function	40 images	DWT	PNN	Ranged from 98% to 100%
Rahil, 2012 [18]	NA	289 dermoscopy images included (114 malignant, 175 benign)	*Different features number based on* WT *combined with statistical measures.*	SVM	85% - 88.30%
				RF	84% - 88.30%
				LMT	79% - 85.11%
				HNB	82% - 88.30%
Ms. H. R. Mhaske, 2013 [19]	Median filter, smooth images, histogram equalization, contrast enhancement and Segmentation	150 mages	96 features and 2- levels of WT decomposition with statistical parameters.	BPNN,	60% - 75%.
				SVM,	80% - 90%.
				K-means clustering	52.63%
Grzegorz Surówka, 2014 [20]	artifacts removed	102 melanoma 83 dysplastic nevus	WPT with different bases	Ensemble method	NA
Maen Tukruri, 2014 [21]	median filter wiener filter segmentation is done by K-means clustering	448 images from Sydney hospital***	11 features WT+PCA	SVM	80.9%
			25 features by CT + PCA	SVM	65.2%
			WT+ color feature	SVM	76.4%
			CT+ color feature	SVM	66.3%
Maen Tukruri, 2016 [22]	Winner filter Median filter to smooth images segmentation by K-means clustering	306 digital images 93 melanoma 213 for benign	WT+ color feature	SVM	85.3%
			CT	SVM	76.6%
			GLCM	SVM	78.7%
Abbas, 2016 [23]	Resize images to (768 x 512) pixels. Segmentation with	350 images for Melanocytic and non-melanocytic lesions for	Color feature RGB to HSV +	MV–SVM	93%

Author, year	**Preprocessing and segmentation**	**Dataset information**	**Feature extraction**	**Classifier**	**Results and accuracy**
	ROI	seven categories	Gabor wavelets transform (GWT)		
Amir Reza Sadri, 2017 [24]	Hair removing, segmentation.	1039 dermoscopy images included (528 melanoma, 511 non-melanoma)	441 features With 2D-WT	SVM	91.34% with 10 features
				FGWN	91.82% with 10 features
Munya A. Arasi, 2017 [25]	Transform to intensity color, median filter, contrast adjustment, morphological operations	206 images from DermIS includes 119 malignant 87 benign****	DWT + PCA	ANN	98.8%
				ANFIS	95.18%
Munya A. Arasi, 2017 [26]	Transform to intensity color, median filter, morphological operations	206 images from DermIS includes 119 malignant 87 benign****	DWT	SAEs	94%
			Texture feature using GLCM		89.3%
Roberta, 2017 [27]	Resizing images to 400 X 299 pixel	1104 images which including 188 for melanoma and 916 for nevus obtained from ISIC challenge 2017.	930 features combined together includes shape, color texture analysis, fractal features, wavelet, Haralick's feature, 14 statistical measures used	Ensemble classification model	Ranged between 93.7% - 94.3%
Saptarshi Chatterjee, 2017 [28]	Hair removing Border detection Segmentation	4094 images for melanoma and nevus	6214 feature extractions used: Wavelet Packet Decomposition statistical features	SVM – the recursive feature elimination RFE	98.28%

Author, year	Preprocessing and segmentation	Dataset information	Feature extraction	Classifier	Results and accuracy
Uzma, 2018 [29]	Hair artifact removal Using 2D-Gaborwavelet or CWT	PH2 database*****	color feature, gray intensity feature, (GW) feature, shape feature.	GMM	99.25%
				SVM	98.29%
				m-Mod	98.50%
Preeti, 2018 [30]	RGB to grayscale, contrast enhancement, histogram adjustment, noise filtering, Segmentation	From Internet websites melanoma/benign	Three features GLCM, wavelet, and Tamura	SVM	100%
				KNN	87.5%
				Ensemble	87.5%
				Decision Tree	75%
Munya, 2018 [31]	Resize images RGB to gray scale, Hair removing by median filter	DermQuest 206 images in the dataset 119 of which are malignant and 87 are benign****	DWT + PCA	NB	98.8%
				DT	92.86%
Roberta, 2018 [32]	Resizing all images to 400 _ 299 pixels	1104 images which including 188 for melanoma and 916 for nevus obtained from ISIC challenge 2017.	Set of features DWT + ABCD + GLCM	KNN	75.8%
				Bayes net	68.2%
				C4.5 DT	86.9%
				MLP	74.5%
				SVM	91.7%
				OPF	92.3%
Akhiyar Waladi, 2019 [33]	Hair removing or	PH2 database*****	DWPT With different wavelet families + GLCM & LBP	RF	91.5%
				GB	91.99%
				LDA	96%

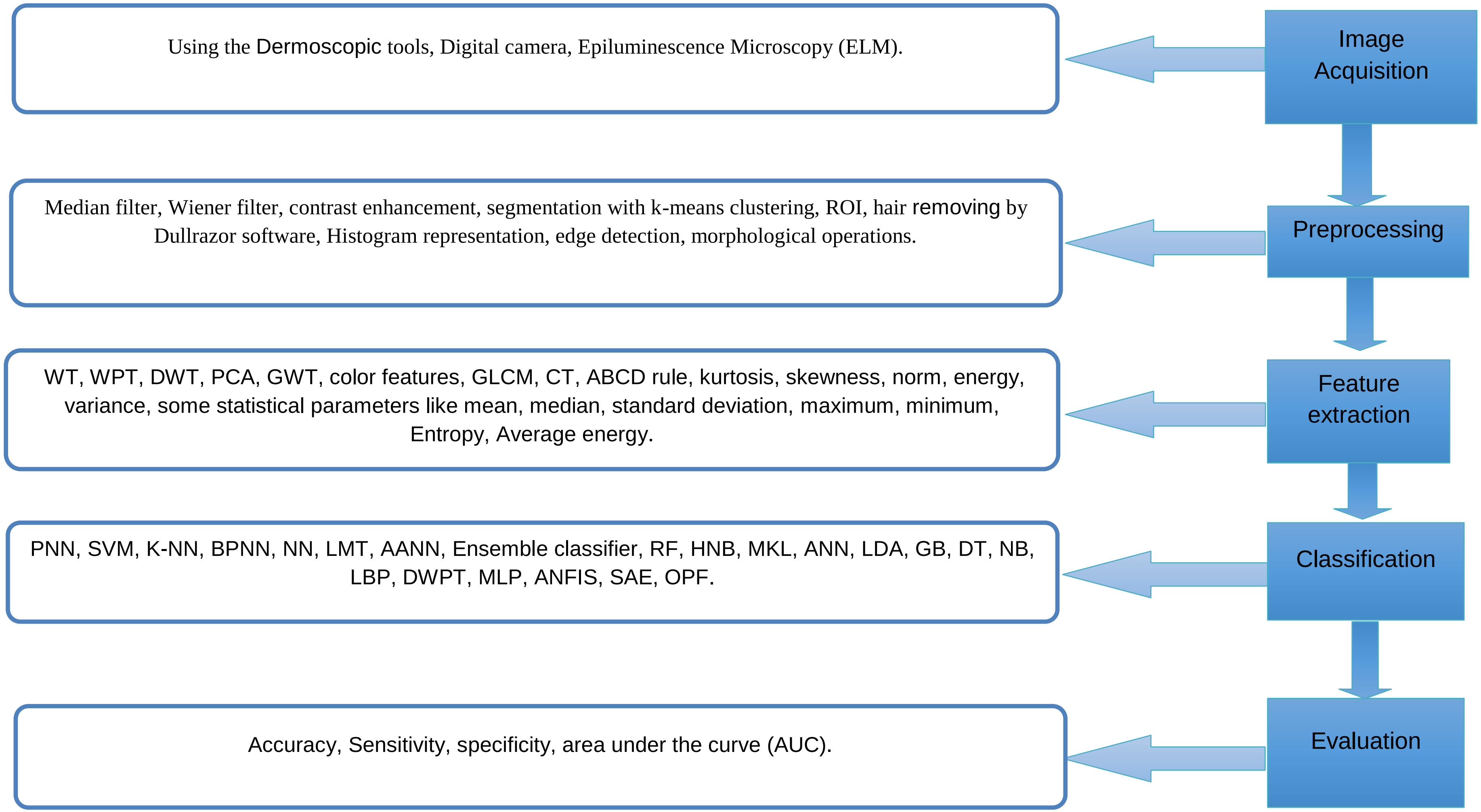

Fig. 1. The techniques used for melanoma detection systems. See the appendix for more details about the abbreviations

Second: Sure entropy

Secondarily, the values of P1 and P2 are selected randomly with a range between (0-1000) as follows: (0, 10, 30, 20, 50, 100, 150, 200, 250, 300, 350, 400, 450, 500, 550, 600, 650, 700, 750, 800, 850, 900, 950 and 1000). There are 576 trails for each wavelet type, have the total of 7488 trials are conducted with loops. These results are collected and reported to calculate the average recognition rate for all thirteen wavelets. Sure, entropy is defined as the following:

$$|s_i| \leq p \rightarrow E_{(s)} = \sum_i min(s_i^2, p^2) \quad (2)$$

Third: Norm entropy

Thirdly, the values of P1 and P2 are selected randomly with a range between (1-3) as the following: (1, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2, 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8, 2.9 and 3). There are 441 trails for each wavelet type, have a total of 5733 trials are conducted with loops. These results were collected and reported to calculate the average recognition rate for all thirteen wavelets. The results are reported and achieved. Norm entropy is defined as the following:

$$E_3(s) = \sum_i |s_i|^p = |s|_p^p \quad (3)$$

The performance of the proposed algorithm is evaluated only by accuracy, which mathematically is described as the following [33]:

Accuracy = ((TP+TN)) / ((TP+TN+FP+FN)) (4)

For the threshold entropy, the range of the output results was between 51% to 83%. We plot all the average recognition rate results in Fig. 2. The best average of the recognition rates is 83.34% that is obtained for threshold parameters P1=400, P2=50. The best result for a single wavelet function was 85.97% achieved with “coif1” when P1=300, P2=10.

For sure entropy, the plot of all the average recognition rate results is illustrated in Fig. 3. The best average recognition rate is for sure entropy (80.63%) at P1=350& P2=50. The maximum value of all these trails is 82.91% achieved with sym10 wavelet function at P1=10 & P2=20. The range of recognition rates is held between (50% - 83%).

For the norm entropy, all the average recognition rate results are plotted in Fig. 4. The best result of the average recognition rate is 81.75% at P1=1.1 and P2= 1. The maximum result of all wavelet and parameters P1 & P2 is 83.45324% is obtained with bior1.5 wavelet function. The range of recognition rates is held between (55% - 83%).

Experiment 2: Comparing with other entropies and wavelet functions

In this experiment, five entropies (Threshold, sure, norm, log-energy, Shannon) are used with 37 wavelet functions from four wavelet families (Biorthogonal spline, Symlet, Coiflet, Daubechies), that are listed in table 2. We selected the best parameters of P1&P2 from the previous experiment of the three entropies. The purpose of this experiment is to identify which parameters can give the best performance. Around 185 trials are conducted in this part. The Shannon and log energy entropies are defined as the following: -

Shannon entropy

$$E_4(s) = -\sum_i s_i^2 \log(s_i^2) \quad (5)$$

Log energy entropy

$$E_5(s) = \sum_i \log(s_i^2) \quad (6)$$

In Table 3 the best 5 results are obtained from experiment 2 to be used.

As we see in Table 3, threshold entropy gives the highest accuracy with 84.71% for Bior3.9 wavelet function.

Experiment 3: Fusion

In this experiment, two different entropy types are combined with different wavelet functions. Six combinations are conducted: Log energy and Threshold, Threshold and Norm, Norm and log energy, Sure and log-energy, Sure and threshold entropies, and finally Sure and Norm. 222 trials were conducted in this experiment. Table 4 summarizes the maximum results for each fusion case.

Experiment 4: Classification method

In our system, we implement PNN as the main classifier. PNN was used for pattern recognition applications as signature recognition [34] and speech recognition [35]. To use different classification methods using classification learner apps in the MATLAB software is implemented for comparison. The learner app was run with 5 cross-validation throughout the all training dataset. These results are obtained for the best performance of the previous experiments. The best recognition rate result was with PNN that reached 85.97%. The results are shown in Table 5.

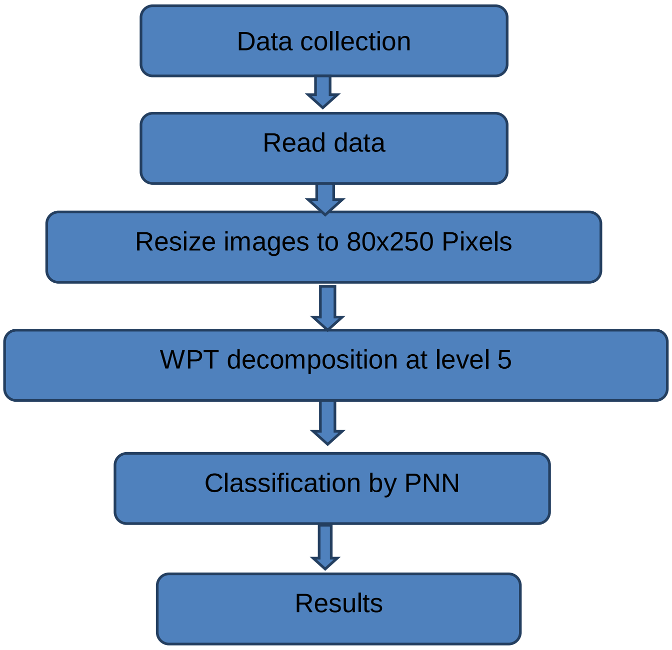

Fig. 2. Diagram of proposed method

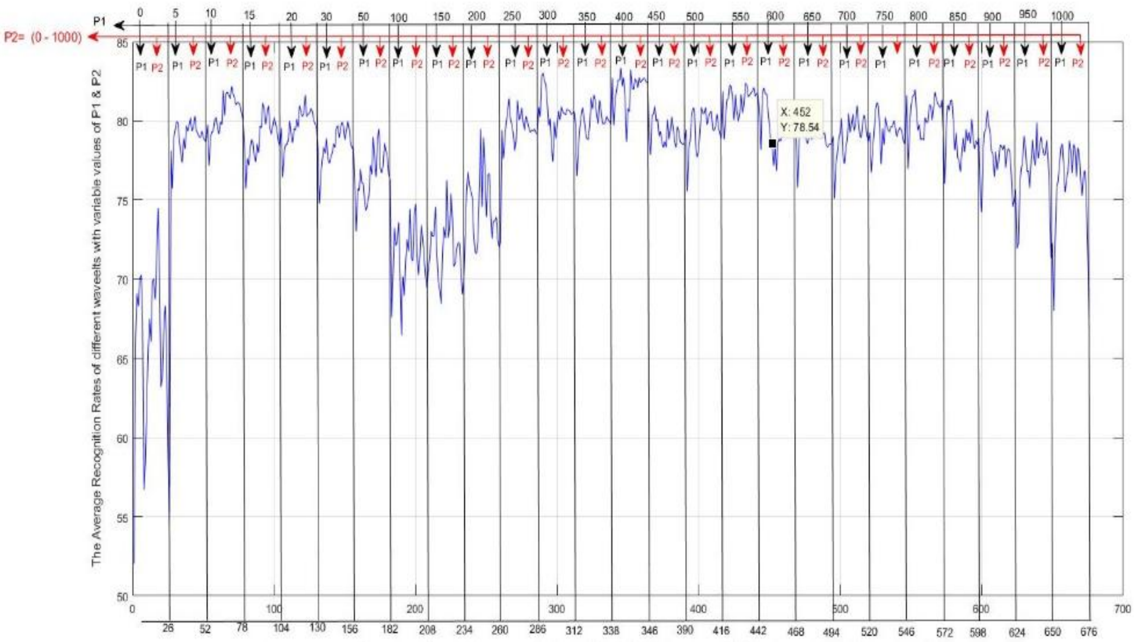

Fig. 3. The average recognition rates of threshold entropy method at (75% Training /25% Testing) system with different thirteen wavelet functions and different parameters of P1 & P2

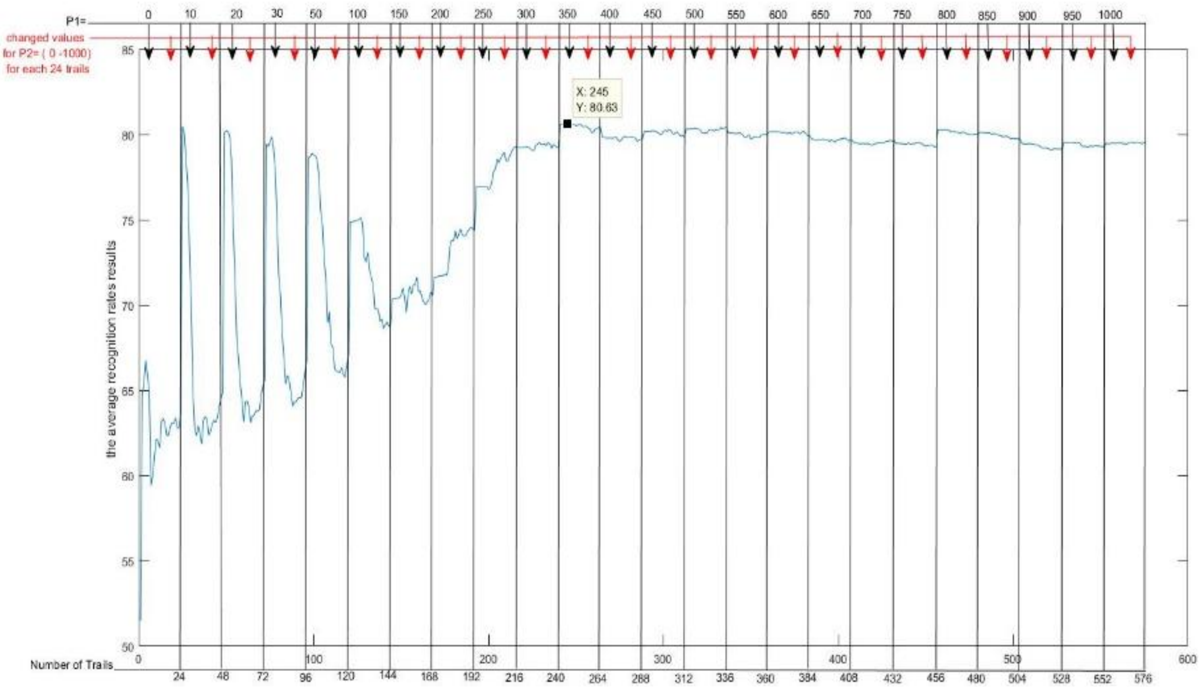

Fig. 4. The average recognition rates of sure entropy method at (75% Training /25% Testing) system with different thirteen wavelet functions and different parameters of P1 & P2

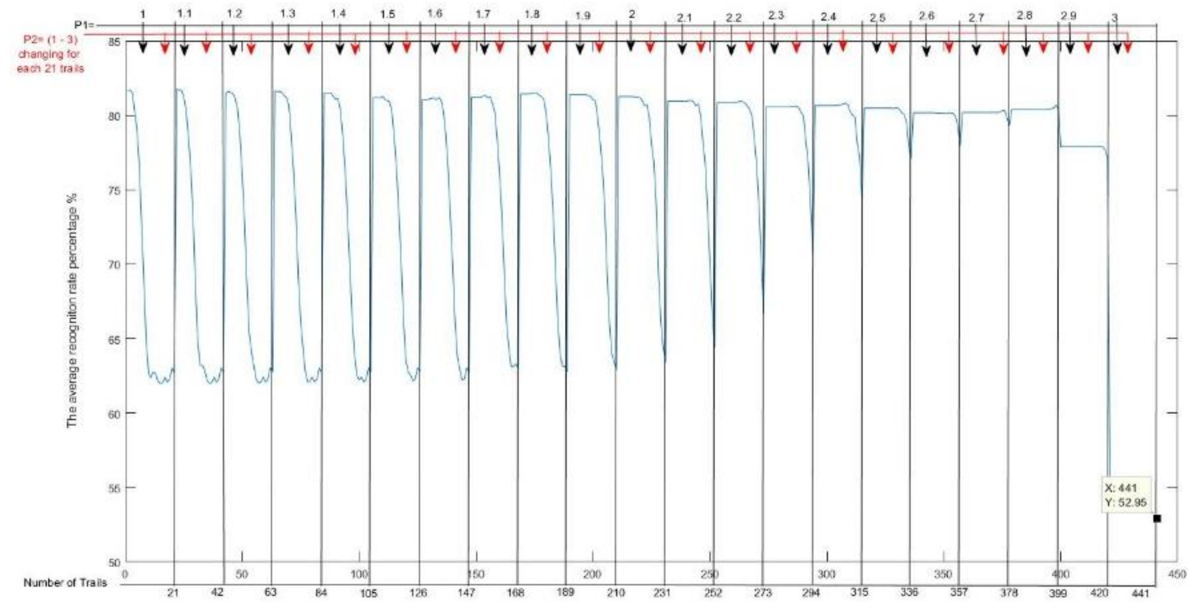

Fig. 5. The average recognition rates of norm entropy method at (75% Training /25% Testing) system with different thirteen wavelet functions and different parameters of P1 & P2

Table 2. Representing all wavelet functions used in this experiment

Wavelets families	Symbol	The types of wavelet
Biorthogonal Spline	Biro	1.1,1.3,1.5,2.2,2.6,2.8,3.1,3.3,3.5,3.7,3.9,4.4
Symlet	Sym	1,2,3,4,5,6,7,8,9,10
Coiflets	Coif	1,2,3,4,5
Daubechies	Db	1,2,3,4,5,6,7,8,9,10

Table 3. The highest results of wavelet functions accuracy performances with each entropy

Entropy	Wavelet functions	Accuracy
Threshold	Bior3.9	84.71%
Sure	Bior3.1	81.65%
Norm	Sym1	82.37%
Log-energy	Sym5	84.71%
Shannon	Bior2.2	81.11%

Table 4. Fusion method of entropy

Fusion method entropy	Wavelet functions	Accuracy
Threshold + Log-energy	Coif3	85.79%
Threshold + Norm	Bior3.3	82.37%
Norm + Log-energy	Bior3.3	82.37%
Sure + Log-energy	Bior1.3 & Bior2.2	81.29%
Sure + Threshold	Bior1.3	81.29%
Sure + Norm	Bior3.1	81.65%

Table 5. Comparing between different classification methods

The classifiers	Accuracy result
Tree: Fine Tree	77.3%
Tree: Medium Tree	79.3%
Tree: Coarse Tree	76.7%
Logistic Regression	69.8%
Linear SVM	79.6%
Quadratic SVM	81.4%
Cubic SVM	79.6%
Fine Gaussian SVM	81.3%
Medium Gaussian SVM	81.1%
Coarse Gaussian SVM	77.9%
Fine KNN	76.9%
Medium KNN	80.2%
Coarse KNN	78%
Cubic KNN	80.3%
Weighted KNN	80.9%
Ensembled Boosted tree	82.8%
Ensembled Bagged Trees	81.6%
Subspace discriminant	77.6%
Subspace KNN	77.5%
Ensemble (Upboosted Trees)	79%

3.1 Discussion

In this paper, we reviewed many research papers that used the wavelet for feature extraction according to the year of publishing. Since the period 2003 – 2010, most of the researchers have used WT without the preprocessing stage with a small dataset from different resources. Their accuracy results with different classifiers ranged between 80% - 95%. The research papers from 2011 until 2015 achieved high accuracy reached to 100% with PNN classifier and DWT with preprocessing stages. In general, the accuracy ranged between 51% - 100%. Many papers have used PCA to reduce feature dimensionality [8,14,19]. The feature numbers for each paper are different, some methods applied a combinational feature. The papers from 2016 to 2019 achieve relatively high accuracy results between 68% - 99%. Table 6 summarizes the feature extraction according to published papers.

There are many classifications implemented methods in the previous literature review. SVM is the most applied classifier for melanoma detection. The accuracy of SVM with different features ranged between 76% - 98.29%. Most of the research papers applied a supervised classification. One paper applied unsupervised methods such as K-means clustering, which achieved low accuracy with 52.36% in reference [17]. Table 7 shows a summary of the most common classifiers.

Table 6. Summary of the most common feature implemented

Feature	References
WT	[5],[6],[7],[9],[10],[11],[16],[17],[20],[22],[25],[28],
WPT	[8], [14], [18], [26], our method
DWT	[12],[13],[15],[23],[24],[29], [30],[31]
GWT	[21],[27]
CT	[19],[20],[25]
PCA	[8],[14],[19],[23],[29]
Texture features	[24],[25],[26],[28],[31]
Color feature	[19],[20],[21]
Shape features	[26],[27]
Statistical parameters	[10],[13],[17],[26]

Table 7. Most common classification method used for melanoma detection

Classifier	References	Accuracy Range
SVM	[6],[7],[8],[12],[13],[16],[17],[19],[20],[21],[22],[26],[27],[28],[30]	76% - 98.29%
BPNN	[10],[14],[17]	51% - 90%
MLP	[30]	74%
ANN	[23]	98.8%
NN	[9]	93.3%
AANN	[10]	80.8%
RF	[13],[16],[31]	86% - 91.5%
LMT	[13],[16]	79% - 88%
HNP	[13],[16]	82% - 88%
PNN	[15], our method	86% - 100%
Ensemble	[18],[26],[28]	75% - 94.3%
DT	[28],[29]	86% - 92%
LDA	[31]	96%
GB	[31]	92%
OPF	[30]	92.3%
M-mod	[27]	98.5%
GMM	[27]	99.25%
KNN	[30],[28]	75% - 87%
SAEs	[24]	89%-94%
ANFIS	[23]	95.18%
FGWN	[22]	91.82%
K-means	[17]	52.36%
NB	[29]	98.8%

4. CONCLUSIONS

In this paper, many researching papers are reviewed; Most of the papers used one type of WT as feature extraction. Other features such as color features, shape features, texture features, and statistical features like mean, median, STD, variance, maximum, Minimum, were implemented with one of the wavelet methods. Various papers used preprocessing to enhance the data set such as color enhancement; contrast enhancement, median filters, and wiener filter to remove unwanted objects such as hair, or bubbles. The segmentation methods were suggested in different papers to assign the region of interest (ROI). SVM is the most used classification method, which achieved accuracy ranged between [76% - 98.29%]. WPT combined with wavelet entropy and the PNN for classification method has been suggested. This method was a very good method for melanoma detection, which achieved 86% accuracy without applying neither preprocessing nor segmentation methods.

5. FUTURE WORK

In the future work, we will implement DWT, GWT to compare with WPT using similar or different wavelet functions.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDIX

The acronym	The definition
GLCM	Gray-Level Co-occurrence Matrix
CT	Curvelet Transform
LMT	Logistic model tree
AANN	Auto-Associative Neural Network
RF	random forest
HNB	Hidden Naive Bayes
MKL	Multiple Kernel Learning
LDA	Linear Discriminant Analysis
GB	Gradient Boosting
DT	Decision Trees
NB	Naïve Bayes
LBP	Local binary pattern
DWPT	Discrete wavelet packet transform
MLP	multilayer perceptron
ANFIS	Adaptive-Network-based Fuzzy Inference System
SAEs	Stacked Auto-Encoders
OPF	Optimum-path forest
KNN	K- nearest neighbor
FGWN	fixed grid wavelet network

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