Abstract—This paper introduces a new approach for the segmentation of skin lesions in dermoscopic images based on wavelet network (WN). The WN presented here is a member of fixed-grid WNs that is formed with no need of training. In this WN, after formation of wavelet lattice, determining shift and scale parameters of wavelets with two screening stage and selecting effective wavelets, orthogonal least squares algorithm is used to calculate the network weights and to optimize the network structure. The existence of two stages of screening increases globality of the wavelet lattice and provides a better estimation of the function especially for larger scales. R, G, and B values of a dermoscopy image are considered as the network inputs and the network structure formation. Then, the image is segmented and the skin lesions exact boundary is determined accordingly. The segmentation algorithm were applied to 30 dermoscopic images and evaluated with 11 different metrics, using the segmentation result obtained by a skilled pathologist as the ground truth. Experimental results show that our method acts more effectively in comparison with some modern techniques that have been successfully used in many medical imaging problems.

Index Terms—Dermoscopy, image segmentation, melanoma diagnosis, orthogonal least squares (OLS), wavelet network (WN).

I. INTRODUCTION

 Among all the types of skin cancer, malignant melanoma (MM) is the most dangerous and deadly. Fortunately, despite its increasingly spread, it is not an untreatable disease if diagnosed at rudimentary stages. In the past few decades, the clinical diagnoses of MM were mostly based on the ABCD rule [1], in which parameters of symmetry, border irregularity, color, and dimension were analyzed, or on the seven-point checklist [2] where various features such as color, shape, and texture were extracted. Later on, the more precise and advanced imaging technique, namely dermoscopy, offered a noninvasive method for in vivo observation of pigmented skin lesions used in dermatology. Recently, due to certain shortcomings of dermoscopy such as its time-consuming, complex, and subjective interpretation processes, computer-aided diagnosis systems have gained great popularity [3]. The standard approach in automatic dermoscopic image analysis has usually three stages [4]: 1) image segmentation; 2) feature extraction and feature selection; and 3) lesion classification. Due to different shapes and colors of skin, segmentation is the most important stage of all.

There have been a great number of algorithms for segmenting dermoscopy images, such as fuzzy c means clustering [5], thresholding [6], gradient vector flow (GVF) [7]–[8], quantitative assessment of tumor extraction [9], j-image segmentation algorithm [10], independent histogram pursuit algorithm [11], k-means++ [12], statistical region merging [13], dermatologist-like tumor area extraction algorithm [14], adaptive snake [4], thresholding based on type-2 fuzzy logic [15], wavelet transform (WT) fuzzy algorithms [16], iterative classification [17], modified random walker algorithm [18], and hybrid thresholding on optimal color channels [19]. These methods are so numerous that comparing them and discussing their advantages and disadvantages has taken the full length of many articles such as [4] and [20]–[22].

Artificial intelligence field, especially using fuzzy and artificial neural network (NN) approaches for segmentation of medical images, has gain special popularity [23], [24]. One of the most promising computational intelligence methods that has been widely used for various applications in different areas is wavelet network (WN).

WN takes full advantage of the characteristics of WT (in denoising, background reduction, and recovery of the characteristic information) and NN capacity of universal approximation [25]–[28]. For this reason, it has a great ability to be used in many different applications. For instance, in image processing [29]–[32].

WNs have overcome many of the flaws in other intelligent methods such as artificial NNs. The main advantage of WNs over similar architectures such as multilayer perceptrons (MLP) and networks of radial basis functions (RBF) is the possibility of
TABLE I

<table>
<thead>
<tr>
<th>Wavelet Networks Types</th>
<th>AWN</th>
<th>FGWN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activation Function</td>
<td>Continuous WT</td>
<td>Discrete WT</td>
</tr>
<tr>
<td>Network Parameters</td>
<td>Weights, Shifts, Scales</td>
<td>Weights</td>
</tr>
<tr>
<td>Network Algorithm</td>
<td>Gradient Types</td>
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</tr>
</tbody>
</table>

optimizing the WN structure by means of efficient deterministic construction algorithms [33].

According to the literature so far, WNs have not been applied to medical image processing yet. This paper proposes a specific WN for segmentation of dermoscopic images.

As described in [34], WNs are divided into two groups: adaptive wavelet networks (AWN) and fixed-grid wavelet networks (FGWN). The characteristics of these networks are shown in Table I.

Due to numerous shortcomings of AWN (for example, complex calculations, sensitivity to initial values, and the problem of measuring initial values), their application is limited [34]. In an FGWN, the outer parameters of the network (number of wavelets, scale, and shift parameters value) are determined beforehand, and only inner parameters of the network (weights) are specified by algorithms similar to the least squares. In fact such networks do not need training [33].

In AWN, in the same way as ordinary NNs or RBF networks, initial values of network parameters (including weights of neurons, shifts, and scales of wavelets) are selected randomly or using other methods. These parameters are then updated in the training stage by means of techniques such as gradient descent or back propagation (BP). Then, the optimized values of network parameters are calculated.

Contrary to AWN, in an FGWN, the number of wavelets, as well as the scale and shift parameters, can be determined in advance and the only unknown parameters are the weight coefficients which are calculated through methods such as least squares. So in our proposed FGWN, there is no need to specify random initial values for parameters or to use gradient descent, BP, or other iterative methods. Normally, in training stage of an adaptive network, all the parameters change; on contrary, in FGWN only, the weights are specified during a noniterative process. Thus, it could be concluded that these WNs do not need training procedure.

This study employs a specific WN for dermoscopy image segmentation: a three-layer FGWN with one hidden layer. At first the input data are normalized. Then, after selecting a proper mother wavelet (which is usually Mexican Hat because of its desirable characteristics such as convenient calculation, adaptability to Gaussian structures, and robustness against noise [35]), a wavelet lattice is formed. Wavelet lattice is a hypershape of wavelets, scale, and shift parameters value. The huge dimensions of this hypershape should be decreased and effective wavelets should be selected. All of these are accomplished through two stages of screening. This paper is unique in that it employs two stages of screening. This gives ground to increase the globality of the wavelet lattice and to estimate the function in a more accurate way which is most beneficial and significant for larger scales.

Then, the OLS algorithm is used to determine the optimized parameters of the network. However, owing to the localized nature of the wavelet basis functions, WNs may not be well suited for dealing with high-dimensional data. The efficient procedure of selecting wavelets in the OLS algorithm, causes this method is not very sensitive to the input dimension [36]. The OLS algorithm transforms the set of regressor vectors into a set of orthogonal bases vectors, so that it is possible to calculate the contribution degree of each basis vector to the output energy. In comparison with BP, OLS is a much faster approach [37].

In order to segment the dermoscopic images, parameters R, G, and B of a dermoscopy image are considered as the inputs of FGWN. The network structure is then determined by means of a ten-stage algorithm, and finally, the output of the network will specify the exact boundary of the skin lesion. Among all the available images, 30 images were chosen to be segmented by an experienced specialist. The algorithm presented in this study is compared with the expected segmentation; ground truth (GT) obtained by a experienced pathologist and four state-of-the-art techniques that have been successfully used in many medical imaging problems; adaptive thresholding (AT) [6]; GVF; fuzzy-based split-and-merge algorithm (FBSM) [38]; and NN. Evaluation process is carried out by 11 different metrics.

The organization of this paper is as follows: The basic concepts of WN is introduced in Section II. In this section, the WN structure with the algorithm necessary for formation of network and determination of its parameters is presented. In Section III, the proposed segmentation process based on WN is introduced. The simulation results of the proposed method in comparison with other approaches are illustrated in Section IV. Finally, in Section V, a summary and conclusion of the findings of the study is presented.

II. WAVELET NETWORK

A. Structure of WN

The output signal of a WN with one output \( y, d \) inputs \( x = (x_1, x_2, \ldots, x_d)^T \) and \( q \) wavelets (wavelet neurons) in the hidden layer is

\[
y = \sum_{i=1}^{q} w_i \psi_{m_i, n_i}(x) = \sum_{i=1}^{q} w_i 2^{-m_i/2} \psi(2^{m_i}x - n_i) \tag{1}
\]

where \( w_i, i = 1, 2, \ldots, q \), are weight coefficients, \( \psi_{m, n} \), are dilated and translated versions of a mother wavelet function \( \psi: \mathbb{R}^d \rightarrow \mathbb{R} \), and \( m, n \), are scale and shift parameters, respectively. This network structure is illustrated in Fig. 1.

According to above definitions, any function \( f \in L^2(\mathbb{R}^d) \) can be approximated by an arbitrary precision using a WN [33].

As mentioned in [25], in real-world applications, the distribution of the noise is often unknown or highly skewed, and thereby, more seriously contaminated data such as outliers may occur. NNs are known to suffer from lack of robustness toward outliers. In contrast, due to time-frequency localization of the WT and the self-learning characteristic of NNs, WN is more effective and robust than NN.
B. Algorithm for Building an FGWN

A major advantage of WNs over other neural architectures is the availability of efficient construction algorithms for defining the network structure [39]. In FGWN, after determining the structure, the weights \( w_k \) in (1) can be obtained through linear estimation techniques. In this study, a constructive method is employed to build an FGWN. It can be described as follows.

Algorithm 1: Suppose we have \( M \) input–output data in the form \( \{ (x^{(k)}, y^{(k)}) | k = 1, 2, \ldots, M \} \), where \( x^{(k)} = [x_1^{(k)}, \ldots, x_d^{(k)}]^T \) is the input \( d \)-dimensional vector and inputs matrix is the form \( X = [x^{(1)} \ldots x^{(k)} \ldots x^{(M)}] \). The output vector is considered as \( y = [y^{(1)} \ldots y^{(k)} \ldots y^{(M)}]^T \). The FGWN structure is determined by a ten-stage algorithm.

1) (Normalization) In many cases, input data of WN vary within a wide range and this variability reduces the efficiency of WN. Thus, this first stage is considered as the data preprocessing stage in which the input data are normalized to a certain range in order to avoid data scattering. If for \( k \)th input: \( T_k = \max_{q=1,\ldots,d} x_q^{(k)} \), \( t_k = \min_{q=1,\ldots,d} x_q^{(k)} \), then for mapping the input data to range \([a, b]\), the following equation is used [40]:

\[
x_q^{(k)}_{\text{new}} = \frac{b - a}{T_k - t_k} x_q^{(k)} + \frac{a T_k - b t_k}{T_k - t_k}
\]

where \( x_q^{(k)} \) is the \( j \)th input of \( k \)th sample, \( x_q^{(k)}_{\text{new}} \) is its value after the normalization process is carried out. In the same way, all of the vector values \( x^{(k)} \) = \([x_1^{(k)}, \ldots, x_q^{(k)}_{\text{new}}, \ldots, x_d^{(k)}] \) fall within the range \([a, b]\). From now on, the \( x^{(k)}_{\text{new}} \) is shown as \( x \).

In cases that data scattering is not significant, this stage is not necessary and it can be skipped over.

2) (Selecting the mother wavelet) Due to better regularities and also the ease of frame generation in comparison with wavelet basis (orthonormal or biorthonormal), in (1) multidimensional single scaling wavelet frame is employed [36].

In this study, the \( d \)-dimensional Mexican hat radial wavelet is used to implement WN. It is expressed as

\[
\psi(x) = \eta |x| = (d - |x|^2) \exp(-||x||^2/2).
\]

3) (Choose the scale and shift parameters) In this stage, minimum and maximum scale levels in the form \([m_{\min}, m_{\max}] \) and shift parameter in the form \( n_i = [n_{1,i}, \ldots, n_{d,i}]^T \), where \( n_t \in [n_{t,\min}, n_{t,\max}] \), \( t = 1, \ldots, d \) and \( j = 1, \ldots, \Pi_{t=1} (n_{t,\max} - n_{t,\min} + 1) \), are to be employed.

4) (Formation of wavelet lattice) In this step regarding a hypershape on wavelet parameters space that was selected in the previous stage, the wavelet function is calculated for all the input vectors according to following equation:

\[
\psi_{m,n}(x) = 2^{-m_d/2} \psi(2^m x - n_i)
\]

where, \( i = 1, \ldots, m_{\max} - m_{\min} + 1 \). In this equation, \( \psi_{m,n}(x) \) is calculated by (3). This spatial figure is called wavelet lattice.

In Fig. 2, a wavelet lattice is shown for \( d = 2 \), where \( d \) is input dimension. In fact, for formation of wavelet lattice, we should calculate the \( \psi_{m,n}(x) \) for all inputs and for all green point in this figure.

As is evident from the Fig. 2, the number of nodes in a wavelet lattice is too many; therefore, it is obligatory that the number of these nodes be lowered and the shift and scale parameters of effective wavelets be selected. It is done through two stages of screening as follows.

5) (Primary screening) In this stage, for every scale level selected in stage 4, \( I_k \) set is formed for each input vector according to

\[
I_k = \{ (m, n) : |\psi_{m,n}(x)| \geq \epsilon \max_i |\psi_{m,n}(x)| \}
\]

where \( \epsilon \) is a chosen small positive number (typically \( \epsilon = 0.5 \)). Also for the reason of simplicity in writing, the index
of shift and scale parameters is eliminated. In fact, in this stage, the effective support of wavelets is selected [36].

6) (Secondary screening) In this stage, the shift and scale parameters of wavelets that are selected in at least two set of the sets in stage 5 are determined. In this way, set $I$ is formed as follows:

$$I = \{ (m, n) : \text{if} [ (m, n) \in I_k, (m, n) \in I_{k'}] \Rightarrow r \neq l \} \quad (6)$$

For example, in Fig. 2, if the nodes with red circles are assumed to be members of set $I_k$, and nodes with blue circles are members of set $I_{k'}$, the nodes with circles in both red and blue colors will be the members of set $I$.

The fact that screening in this study is performed in two stages is its novel and distinguishing feature which makes the wavelet lattice globalized. It also brings about better estimate of the function that serves best for larger scales.

7) (Formation of wavelet matrix) Suppose that the number of selected wavelets in the last stage as $L$. In addition, to make the writing simpler, the couple index of $(m, n)$ is replaced with single index of $\{ l = 1, \ldots, L \}$.

In this stage, $W_{I \times L} = [\psi_1, \psi_2, \ldots, \psi_L]$ matrix is calculated for all the input vectors and for all the selected shift and scale parameters that are in set $I$. In this matrix, $\psi_l$ vectors is considered as regressors [36]. This matrix is called wavelet matrix and calculated as follows:

$$W = \begin{bmatrix}
\psi_1(x^{(1)}) & \cdots & \psi_L(x^{(1)}) \\
\vdots & \ddots & \vdots \\
\psi_1(x^{(M)}) & \cdots & \psi_L(x^{(M)})
\end{bmatrix}. \quad (7)$$

The output vector is then constructed as

$$y = \sum_{i=1}^{s} w_i \psi_i = W \theta \quad (8)$$

where weight vector $\theta_{L \times 1} = [w_1 \ldots w_L]^T$ is included of the weights between the wavelets of hidden layer and output layer.

8) (Performing OLS algorithm) In the previous stages, the output of the WN was expressed in terms of expanding the wavelet matrix members. After two stages of screening, some of matrix members are still redundant. The reason is that only the input information and not the output information is taken into account for forming the wavelet matrix. Also in order to avoid overfitting problems that result from an overparameterization of the model, it is important to select a reduced and effective subset of wavelets [33]. A fast and efficient model structure determination approach has been implemented using the OLS algorithm. This approach has been extensively studied and widely applied in nonlinear system identification [37].

According to the OLS algorithm, to select the best subset of $W$, assuming that the size of this subset is known and denoted as $s$, the following steps should be taken.

At first, the most significant wavelets in $W$ is selected. Next, all other (not selected) wavelets are made orthogonal to the selected one. In the second step of the algorithm, the most significant of the remaining wavelets is again selected; then, in this step, all nonselected wavelets are made orthogonal with respect to the selected one, so that second selected wavelet with addition to the first one can determine the best approximation. And then, the algorithm goes on for the rest of wavelets. Since all remaining wavelets are made orthogonal to all selected ones in each step of the algorithm, the improvement of each selectable wavelets is isolated. The iterative procedure is described in [36].

After employing this stage, WN is constructed as

$$y = \sum_{i=1}^{s} w_i \psi_i(x) \quad (9)$$

where $s$ is the number of wavelets in the hidden layer and $w_i$ is the weight of wavelets.

After performing the OLS algorithm, $W$ is composed of orthonormal matrix $Q$ and upper triangular matrix $A$. So, (9) can be rewritten as

$$y = QA^T \theta. \quad (10)$$

9) (Selecting the number of wavelons) Wavelons are the nodes creating the hidden layer of the WN. By choosing the ideal number of wavelons, the system performance index is calculated as (11). Then, the number of wavelons will change until the desired error measure is achieved

$$\text{MSE} = \frac{1}{M} \sum_{k=1}^{M} (\hat{y}^{(k)} - y^{(k)})^2. \quad (11)$$

Here, $\hat{y}$ is the function approximation and $s$ is the number of wavelets in hidden layer. The index of model performance in this method is mean squared error (MSE). Another method for selecting the number of wavelons is calculated by the generalized cross validation method which is presented in [36].

10) (Calculating wavelons weight coefficient) This stage is the last stage of the algorithm. The weight of wavelons is measured by the least-squares method. This is done by the following equation:

$$Q^T y = A^T \theta. \quad (12)$$

III. SEGMENTATION ALGORITHM

The algorithm from the previous stage is used in the present stage for segmentation of the dermoscopic images. From images database, a number of images are randomly chosen for formation of FGWN. At first the values of R, G, and B matrices of each color dermoscopic image are mapped into $[0, 1]$ range by performing normalization process. Thus, (2) changes to

$$x_q^{(k)} = \frac{x_q^{(k)} - t_k}{T_k - t_k} \quad (13)$$
where \( x_{q_{\text{new}}}^{(k)} \) is the value of each color matrix after normalization (located in \([0,1]\) range), and \( t_k \) and \( T_k \) are minimum and maximum values of these matrices, respectively.

Then, an FGWN is formed with three inputs, a hidden layer, and an output. In order to form the FGWN, the values of three color matrices are considered as network inputs.

These matrices are related to the five chosen images from the selected images for segmentation. From these images, some pixels are selected randomly (ranging from 1000 to 5000 pixels for a 485 \( \times \) 716 image). If the pixel is inside the lesion, network output will be considered as 0, and if the pixel is outside the lesion, the output will be considered as 1.

In this way, the FGWN is formed. After that, the value of the three matrices \( R \), \( G \), and \( B \) for each pixel are considered as FGWN inputs, and the output of FGWN is a binary image that shows the segmented of original image (see Fig. 3).

IV. EXPERIMENTAL RESULTS

A. Database and Ground Truth

This study employs a collection of dermoscopic images taken from a specialized skin laboratory as its database. This database includes 1039 dermoscopic images from different parts of the body taken under the same environmental conditions. All of these images are 24-bit RGB color, with 485 \( \times \) 716 size, and are taken from patients suspected to melanoma. Whether or not the patients have caught the disease is determined by biopsy and is diagnosed by the dermatologist.

A large number of database images are very similar. Accordingly, when the images were perused and segmented by a skilled dermatologist (Dr. M. Mokhtari, a skilled specialist with over ten years of experience in dermoscopic image analysis), they were naturally categorized to 30 distinct groups. In fact, each of our selected 30 images is a representative of a group. From each group, one image was randomly chosen, and for each image, a manual segmentation was performed in full-sized printed images. These images were scanned with the same resolution as the primary images and used as ground truth of automatic segmentation.

B. Preprocessing

It is worth noting that the database images employed in this paper were free of any noise or artifacts. In case of noisy images (images which are not of desired quality or the results of segmentation are not satisfactory), or necessity of elimination of the hairs, a preprocessing stage like Dull-Razor filter [41], morphological filters and median filter [4], must be used.

If the image has noise, depending on the type of the noise, different algorithms are used to remove it.

A kind of noise that might appear on dermoscopic image during transmission, storage, and processing is impulse noise. The researchers have canceled this noise based on the combination of FGWN and median filter. The results of the procedure are presented in [42]. Three common other types of noises found in medical imaging such as dermoscopic images are Gaussian, Poisson, and Rician [43].

C. Results

An example of the segmentation results obtained by the various methods is given in Fig. 4 which shows one of the ground truth segmentation together with the results by all five other methods. The algorithms that we compared with the proposed method are AT [4], GVF [7], FBSM [38], and NN.

AT achieves good results when there is a good contrast between the lesion and the skin [4]. The GVF is a well-known technique proposed in [44] which has been frequently used in many medical imaging. For segmentation with GVF algorithm, we have used the source code provided at http://iacl.ece.jhu.edu/projects/gvf/. FBSM is another method which is presented in [38]. In FBSM, dermoscopic image segmentation is based on fuzzy methods, which yields fairly good results. Since the central idea of WNs has its roots in NNs, an NN is also used for segmentation. The NN employed here is a three-layered MLP with three inputs, a hidden layer (with 22–25 neuron), and an output. R, G, and B values of an image are considered as the NN inputs. If the pixel is inside the lesion, MLP output will be considered as 0, and if the pixel is outside the lesion, the output will be considered as 1. Among the selected images, 30% were used for training of the MLP and the rest were employed for testing it. Training the NN was carried out by means of the fastest training function available in MATLAB.

Among the 30 images selected for segmentation using the proposed FGWN, five images were used for building the network structure (formation of the wavelet lattice, determination of the shift and scale parameters, and calculation of the network weights), and the rest were used for testing it. In our experiments, 10–12 wavelons are enough to achieve good results.

Referring to Fig. 4, it can be observed that the segmentation produced by the proposed method (FGWN) is smoother than those by four other algorithms. Clearly, smoother border is more realistic and also conforms better than the manual segmentation derived by the specialist.

D. Postprocessing

Since extracting the features of lesion is the most essential part of diagnosing melanoma, extracting the exact boundary of lesion is a vital task. For this, after segmentation with an FGWN and according to the proposed algorithm in Section III, the space between two shapes is filled, extra parts are eliminated, and the noise is removed. Then, the exact boundary of lesion is extracted. This is done by appropriate morphological processes, including

![Fig. 3. Presented FGWN for segmentation of dermoscopic images.](image-url)
erosion, dilation, closing and opening, and region filling [45]. Size, shape, and kind of structuring elements were based on images dimensions and type of their objects that are selected tentatively and provisionally.

E. Evaluation of Results

For our experimental evaluation, we used a PC with Intel(R) Core(TM)2 Duo CPU T9550 (2.66 GHz) and 4 GB RAM. All the methods were realized by MATLAB 7.12.

As mentioned before, segmentation is the most important and critical stage of the three stages of automatic diagnosis of melanoma which has a very significant role in the final outcome. Because of this reason, the performance of this state should be examined by means of appropriate criteria. In this study, 11 criteria of standard evaluation are employed which have been used in a great number of related research.

To define these metrics, let GT and SA denote the ground truth segmentation obtained by the medical expert and results of a segmentation algorithm, respectively. Both GT and SA are binary images and all the pixels inside the curve have label 1 and all the others have label 0.

These criteria are defined based on four parameter: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Fig. 5 clearly illustrates these parameters as well as the method of their measurement.

The formulas of measuring the 11 criteria for evaluation are presented in Table II. The database of 30 images was processed using all the methods under evaluation. This table shows the median of these criteria for the five approaches that are compared in this study.

As depicted in this table, the values of our proposed algorithm for all the evaluation criteria are better than other methods. In a similar vein, it is evident from this table that the FGWN algorithm has an appropriate level of specificity. This means that the FGWN algorithm diagnoses the lesion boundary properly;

![Fig. 5. TP is the number of pixels that were classified both by GT and SA as lesion pixels TP = GT \cap SA, and TN is the number of pixels that were classified both by GT and SA as nonlesion pixels TN = (GT \cup SA). FP is the number of pixels where a nonlesion pixel was falsely classified as part of a lesion by SA FP = SA \cap GT, and FN is the number of pixels where an lesion pixels was falsely classified as nonlesion by SA. FN = GT \cap \overline{SA}.](image-url)
therefore, the lesion boundary that is the most significant feature in detecting melanoma is extracted by FGWN with an acceptable accuracy.

Our method is quite simple and considering the satisfactory results of this study, it is very applicable for detecting melanoma by means of the computer or robot.

V. CONCLUSION

In this study, a new approach is proposed for segmentation of dermoscopic images based on FGWN. The R, G, and B values of a dermoscopy image are considered as FGWN inputs and the OLS algorithm is used to determine the network weights and to optimize the network structure. The proposed method with four methods (AT, GVF, FBSM, and NN) and hand segmentation by a specialist and based on 11 criteria showed better results in comparison to similar previous studies. The developed algorithm hence provides a useful tool as a first stage in the automatic or semiautomatic analysis of skin lesion images.

REFERENCES


### TABLE II

<table>
<thead>
<tr>
<th>Evaluation</th>
<th>TPR</th>
<th>TNR</th>
<th>FPR</th>
<th>FNR</th>
<th>Sensitivity</th>
<th>Specificity</th>
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<th>Precision</th>
<th>Similarity</th>
<th>Border Error</th>
<th>Hammour Distance</th>
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<tbody>
<tr>
<td>Formula</td>
<td>TP</td>
<td>GT</td>
<td>TP</td>
<td>FN</td>
<td>TP + TN</td>
<td>TP + TN</td>
<td>TP + FN</td>
<td>TP + FN</td>
<td>2TP</td>
<td>FP + FN</td>
<td>FP + FN</td>
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<tr>
<td>AT</td>
<td>83.33%</td>
<td>79.58%</td>
<td>20.42%</td>
<td>16.67%</td>
<td>83.33%</td>
<td>99.28%</td>
<td>98.74%</td>
<td>80.32%</td>
<td>81.80%</td>
<td>37.08%</td>
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</tr>
<tr>
<td>GVF</td>
<td>83.96%</td>
<td>81.95%</td>
<td>18.05%</td>
<td>16.04%</td>
<td>83.96%</td>
<td>99.37%</td>
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<td>82.30%</td>
<td>83.12%</td>
<td>34.09%</td>
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<tr>
<td>FBSM</td>
<td>88.41%</td>
<td>89.83%</td>
<td>10.17%</td>
<td>11.59%</td>
<td>88.41%</td>
<td>99.66%</td>
<td>99.30%</td>
<td>89.69%</td>
<td>89.04%</td>
<td>21.76%</td>
<td>25.35%</td>
</tr>
<tr>
<td>NN</td>
<td>93.36%</td>
<td>92.06%</td>
<td>7.94%</td>
<td>6.64%</td>
<td>93.36%</td>
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<td>92.76%</td>
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<td>FGWN</td>
<td>94.34%</td>
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<td>99.84%</td>
<td>99.67%</td>
<td>94.79%</td>
<td>94.56%</td>
<td>10.85%</td>
<td>11.85%</td>
</tr>
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</table>

For each algorithm the median value are given.


