Objective Assessment of Skin Repigmentation Using a Multilayer Perceptron

Abstract

Background: Vitiligo is a pathology that causes the appearance of achromic macules on the skin that can spread on to other areas of the body. It is estimated that it affects 1.2% of the world population and can disrupt the mental state of people in whom this disease has developed, generating negative feelings that can become suicidal in the worst of cases. The present work focuses on the development of a support tool that allows to objectively quantifying the repigmentation of the skin. **Methods:** We propose a novel method based on artificial neural networks that use characteristics of the interaction of light with the skin to determine areas of healthy skin and skin with vitiligo. We used photographs of specific areas of skin containing vitiligo. We select as independent variables: the type of skin, the amount of skin with vitiligo and the amount of repigmented skin. Considering these variables, the experiments were organized in an orthogonal table. We analyzed the result of the method based on three parameters (sensitivity, specificity, and F1-Score) and finally, its results were compared with other methods proposed in similar research. **Results:** The proposed method demonstrated the best performance of the three methods, and it also showed its capability to detect healthy skin and skin with vitiligo in areas up to 1 × 1 pixels. **Conclusion:** The results show that the proposed method has the potential to be used in clinical applications. It should be noted that the performance could be significantly improved by increasing the training patterns.

Keywords: *Artificial neural network, multilayer perceptron, objective assessment, skin repigmentation, vitiligo*

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Introduction

The skin is the largest organ of the human body. Its main function is to protect the internal organs from agents that are in the environment. However, the cells that compose it can present disorders in their functions, producing multiple pathologies such as cancer, psoriasis, and vitiligo. Among cutaneous diseases, one of the most frequent pigment pathologies worldwide is vitiligo[1,2] which affects between 0.5% and 1.2% of the world population. Although it affects without distinction of sex, race or age, and even some studies have reported that there is a higher incidence of vitiligo in India, Mexico, and Japan.[3-5] Vitiligo is characterized by causing the selective destruction of melanocytes (cells responsible for producing a skin protection pigment called melanin), resulting in the appearance of achromic macules that can change shape, increase in size or be distributed in other areas of the body.[6,7]

Vitiligo can be psychologically devastating[5] affecting the mental state of people generating negative feelings such as anxiety and depression,[8-10] fear, and even suicidal thoughts.[11] Although its etiopathogeny is multifactorial, it has been identified that biochemical and cytotoxic changes generated when a person is being subjected to high levels of stress, which becomes the main trigger and exacerbate of this pathology.[12]

The therapeutic treatment for this pathology is carried out from two approaches: the medical and the surgical, including oral treatments, topical, phototherapy, and alternative methods such as relaxation therapies.[4,13,14] The fundamental objective of these, is, first to stop the progress of vitiligo and then to recover affected skin area by repigment it. The effectiveness of the treatment is evaluated through the analysis of the skin, identifying factors such as color changes (peripheral o perifollicular) and size of the affected area. Nowadays,

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subjective, semi-objective, and objective methods have been proposed to evaluate the skin affected by vitiligo. Based on the objective methods, high-precision noninvasive support methods using image processing have been developed by taking advantage of the high sensitivity of image sensors installed in conventional digital photographic cameras.[2] Fadzil *et al*.[15] using an image obtained with a conventional digital camera, they proposed a method to measure the repigmentation of the skin. Using principal component analysis and the technique based on the independent component analysis (ICA) known as FastICA,[16] two images that are based on the melanin and hemoglobin of the skin were obtained. Finally, using image based on melanin, the amount of healthy skin and skin with vitiligo in the photograph was determined. Nurhudatiana,[17] proposed the use of only the blue channel of a red-green-blue (RGB) photograph and with a clustering algorithm called Fuzzy C-Means (FCM) to group the pixels that correspond to healthy skin and skin with vitiligo in two different groups. Once grouped, the group with the lowest centroid value defines the pigmented skin, while the group with the highest centroid value defines the skin with vitiligo. It should be noted that the experiments were carried out using images taken from the internet. In addition to techniques that use RGB photographs, other methods have been developed with the use of spectra diffuse reflection of the skin, models of the skin or other computational algorithms different from FastICA and FCM.[18-20]

The present work focuses on the development of a support tool for the diagnosis and evaluation of the treatment that allows to objectively quantifying the repigmentation of the skin. To this end, we propose a novel method that uses the characteristics from the interaction of light with healthy skin and skin with vitiligo, which then can be captured with a conventional digital photographic camera. The characteristics extracted from the photograph are applied to an artificial neural network (ANN) of multilayer perceptron type (MLP) of supervised learning, which is responsible for determining pixel to pixel the areas affected by the pathology, allowing a quantitative measure of them. In related papers[15,16] have been shown that in an RGB image of the skin, the pixels contain information related to the melanin (mostly responsible for the color skin) and hemoglobin but these techniques used the entire photograph. Based on this, we proposed a method that analyzes a photograph pixel to pixel, and to avoid the problems with the generality of the model and the different skin types, we use statistical metrics that give to the MLP information about of the distribution (central tendency and scattering) of the values of the intensity levels of the pixels in all the image. Thereby, the proposed method uses specific information of a single pixel; in addition to the information provided by the entire photograph.

The use of ANNs due to the good results obtained when analyzing medical images[21-24] have been opted. Among the various types of ANNs, an MLP type because once trained have been chosen, its implementation does not generate excessive computational cost; so, it could be implemented in mobile applications. Besides, we also aimed to evaluate the utility of its nonlinearity characteristics to recognize patterns pixel to pixel in a medical image. The method proposed in this work has been compared with two other methods that exist in the scientific literature to evaluate its performance.[15,16]

Interaction of light with skin

The skin is composed of several layers of tissues, in other terms; the stratum corneum (outer layer of the skin), the epidermis, the dermis, and the subcutaneous tissue or hypodermis. When a beam of light hits the skin, only a small fraction is reflected directly (4%–7%),[25] the rest penetrates and follows a path through the first layers of the skin, until it comes back out, or dims by the chromophores (molecule that absorbs electromagnetic energy) of the skin. The predominant chromophores in the dermis and epidermis are oxyhemoglobin (OHb), deoxyhemoglobin (DHb), and melanin.[25,26]

The efficiency in the absorption of the electromagnetic energy of the chromophores of the skin is a function of the wavelength of the electromagnetic energy,[27] the OHb has a higher absorption in the bands of 412 nm, 542 nm, and 577 nm, whereas the greater absorption of DHb occurs in the 430 nm and 555 nm bands. Melanin, on the other hand, does not show maximum absorption in the visible light region, nevertheless, increases progressively when approaching the short-wave electromagnetic spectrum. Figure 1a shows that in the red spectrum region (600 nm), the absorption of melanin is greater compared to OHb and DHb [Figure 1b].[27]

Thus, when a beam of light interacts with the skin, the information of melanin and hemoglobin (OHb and DHb) is found in the total reflection (resulting light), information that can be recorded in a digital image.

Artificial neural networks

The nervous system of the human body is made up of millions of interconnected nerve cells called neurons. The neuron could be defined as an information processor that is composed of dendrites (input channel), the soma (where the information is processed), and an axon (output channel). On the other hand, the neuron has an excitation threshold (action potential), which is a minimum level that should have a stimulus to activate the neuron and transmits that stimulus to another neuron, in case the stimulus does not beyond the threshold, it will not be transmitted.[28]

If a stimulus is present, the neuron communicates with other neurons (in a process called synapse) and forms connections that allow an adequate response to that

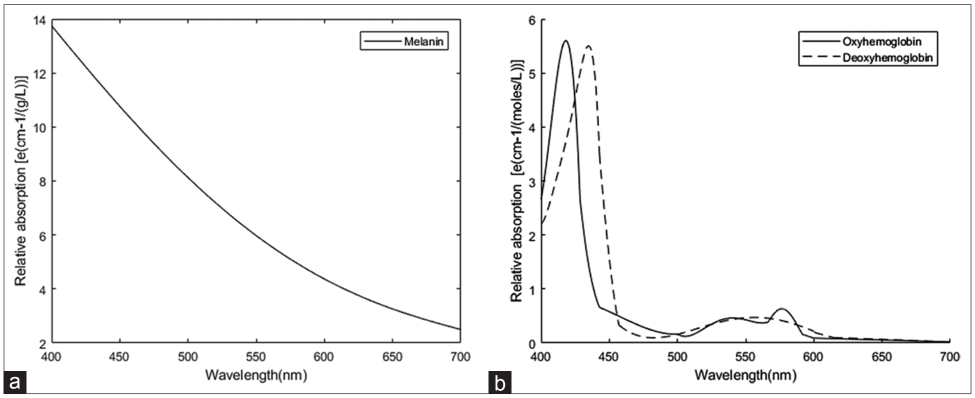

Figure 1: Absorption spectrum of the skinīs predominant chromophores: (a) response profile of Eumelanin, it can be noted that although there is no maximum absorption in the region of visible light, it increases progressively when approaching the electromagnetic spectrum shortwave; Image based on.[28] Absorption spectrum of the skinīs predominant chromophores (b) response profile of oxy-hemoglobin (solid line) and deoxyhemoglobin (dashed line). Image based on[28]

stimulus. If the same stimulus occurs again and again, the neurons can improve or inhibit their response in such a way that the connections between them are the most optimal to provide the best possible response to that stimulus; the process of presenting the stimulus over and over again is called training.

Artificial neurons, on the other hand, are formed from a mathematical model that simulates the behavior of biological neurons, both in their function and their way of processing information. Figure 2 shows a model of the artificial neuron, relating this model to the biological neuron, the set of inputs Xi represents the dendrites, similar to what happens in the synapse in the artificial neuron, it can inhibit or improve its response to mathematically model, by the modification of numerical values called synaptic weights (W).[29] In this way, each of these inputs is multiplied by its respective synaptic weight (Wij) and a weighted sum of these values is performed. In the event that the sum exceeds a certain threshold value (analogous to the excitation threshold), the resulting value is evaluated by an activation function f () (analogous to the action potential) with which the output of the neuron is obtained (Tj).[30] The output of a neuron can be described by the following mathematical function:

$$T_j = f\left(\sum w_{ij} x_i\right) \tag{1}$$

The artificial neuron allows to solve simple and linear problems. Thus, when the artificial neurons are interconnected with other neurons, structures called ANNs can be formed to solve complex problems. There are different types of ANN topology, being that the MLP is the most widely used.[30-32] Although the MLP architecture is diverse, this topology consists of three layers of neurons: input (receives data), hidden (processes information), and output layer (provides the output of the network).[31] Figure 3 shows the architecture of an MLP with a hidden layer where each neuron (represented by a circle) is linked to another through a synaptic weight (W).

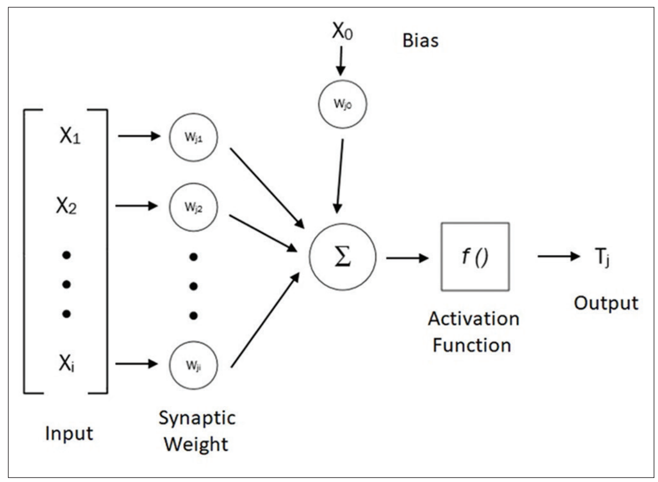

Figure 2: Operation diagram of an artificial neural network

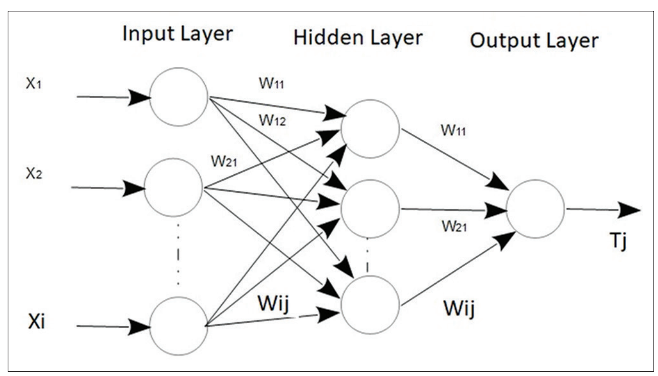

Figure 3: Structure of a multilayer perceptron with one hidden layer

There are several types of activation functions within the ANNs. In the case of MLP, the most commonly used are the sigmoidal function (restricts its output to values of 0 and 1) and the hyperbolic tangent functions 1 (restricts its output to values of −1 and 1).

The MLP has the ability to learn by adjusting the value of their synaptic weights through a training phase. In the training phase, input patterns are presented, and the desired output is indicated for each pattern to the network, this process is repeated in a cyclical way. Thereby, when all the training patterns have been presented to the network, a process called epoch is completed. The number of times required for in the training phase depends on the type of problem being treated, and it could range from 1 time to 10,000 or more; depending on whether the network has reached the value of the desired error. The purpose of training is for the network to generalize the information in such a way that it knows how to respond correctly when data are presented for which it was never trained, making it necessary to choose correctly the parameters of the network (number of neurons, activation function, and training data). In this way, problems of overlearning can be prevented (the neural network gives a correct answer only for the training data but not so for new data) or prevent the network from not being able to generalize because there is not enough training patterns.[30]

In case that images are MLP inputs, the training process consists on using input patterns (groups of pixels) as well as inputs to the ANN, and in turn knowing the desired outputs for each particular pattern. After all the input patterns have been presented to the network, what has been defined as an epoch is obtained. This process will be repeated iteratively until the MLP has adjusted its Wij synaptic weights in such a way that the difference (error) between the desired output and the current output is minimal.

Optimization algorithm

The conjugate gradient methods (CGMs) are currently the most popular iterative algorithms when is necessary to solve linear systems "defined-positive" and symmetric equations.[33] Like the standard backpropagation method, the CGM uses the second derivative of the objective function to approach the minimum value in an iterative process, guiding itself in a conjugated direction with respect to the previous steps. In the case of ANNs, the conjugate gradient can be used in updating weights, to produce a response that generates the least possible error in the network. Being W the matrix that represents the synaptic weights, a(k) the matrix of second derivatives (Hessian matrix) and p(k) a function of a(k) that contains the error function that we want to minimize. In this way, the update of synaptic weights would be given by:

$$W(k+1) = W(k) + a(k)\ p(k) \tag{2}$$

To optimize the iterative process, Moller[34] proposed the scaled conjugate gradient (SCG) method, which differs from conventional CGM in two aspects: the first, for the calculation of the error function (key term in the calculation of a[k]), a long search process is not used, but a simple approximation is made. The second, to ensure good performance is used to (k) as a scalar, which implies a regulation of the Hessian matrix (the Hessian matrix may not always be positive definite). The SCG has been shown to be faster than the standard retro-propagation and other CGMs.

Materials and Methods

Patients

The study protocol was approved by the Research Coordination Center of a Hospital in Cuenca Ecuador. Twenty patients from this institution were selected to obtain the photographs used in the training and validation of the proposed method.

Inclusion criteria: Patients who participated in the study signed an informed letter of consent, they have Type II or type III skin according to the Fitzpatrick scale,[35] their age varies between 18 and 55 years, and they did not have any type of burn (sunburn and phototherapy) near the photographed area.

Proposed method

Reflection of light

The areas affected by vitiligo, typically do not contain melanin or are unable to produce it. When a light strikes the affected skin, as there is no melanin and hemoglobin that absorbs part of the electromagnetic energy of light; therefore, the resulting light is attenuated. Nevertheless, in the case of skin with vitiligo, the only absorption that will exist will be that of hemoglobin, causing the intensity of the resulting light not to be attenuated and thus greater than that of healthy skin.

Figures 4a and 5a show two different types of skin: skin Type II and skin Type III, respectively. In these images, the absence of melanin generates achromic macules due to how the light reflects on the skin. To observe the differences of absorption and reflection of light in the skin in each of the RGB bands, a row of each of the images has been extracted (indicated as a black line on the image) and they have been plotted in Figures 4b and 5b, respectively.

In Figure 4b, it can be seen that in the area affected by vitiligo there is no light attenuation due to the absence of melanin, so the value of the intensity of the pixels in the RGB bands is higher in this area [approximately from pixel 110–140 in Figure 4b]. Similarly, in Figure 5b, it can be seen that the intensity of the pixels in each of the bands is greater in the area affected by vitiligo.

Although there is a similar pattern of light reflection in both cases, the range of intensity values in clear skin is different from darker skin. However, although the magnitudes are different, differences in the reflection of light can be used by an algorithm to differentiate healthy skin from the skin with vitiligo.

Proposed algorithm

We propose the use of an ANN with an MLP topology to analyze each of the pixels of an image and classify them, either as healthy skin or skin with vitiligo; based on the light reflection pattern. Therefore, at the end of the process, the MLP generates a binary image from the original image,

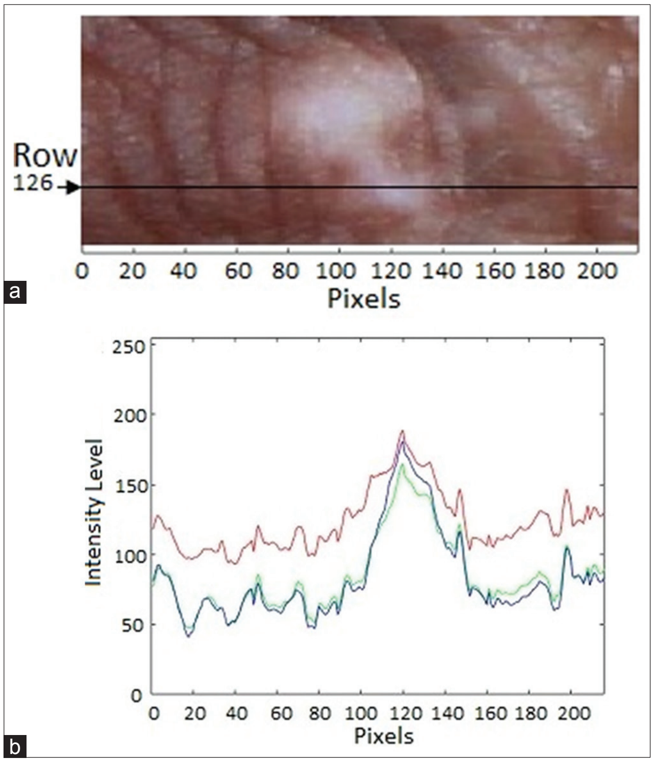

Figure 4: Level of reflection of the skin in red-green-blue images: (a) Original skin image. Level of reflection of the skin in red-green-blue images: (b) Information of the intensities of the red-green-blue image obtained from row 126 represented by a horizontal black line in the original image

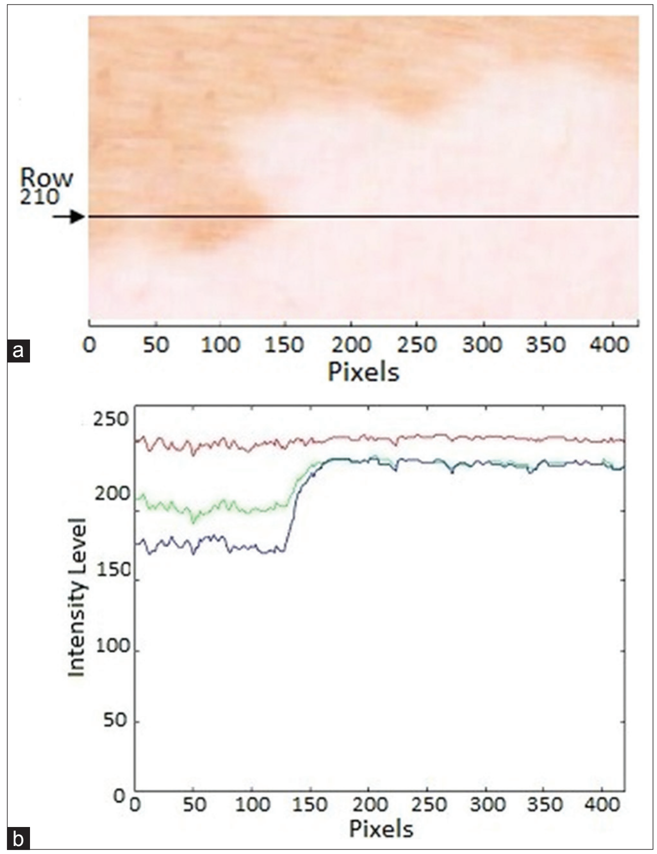

Figure 5: Level of reflection of the skin in red-green-blue images: (a) Original skin image. Level of reflection of the skin in red-green-blue images: (b) Information of the intensities of red-green-blue image obtained from row 202 represented by a horizontal black line in the original image

where the pixels with the value of 0 correspond to healthy skin, and the pixels with the value of 1 correspond to skin affected by vitiligo.

The proposed MLP consists of three layers; input layer, hidden layer, and output layer. In the hidden layer a sigmoidal logarithmic activation function is used because its nonlinear response makes it ideal for the classification of this type of patterns. The RGB components of each pixel of the image are used as input characteristic vectors. Due to the difference in the intensity level of light reflected by healthy skin and the skin affected by vitiligo varies depending on the skin tone, two vectors of additional characteristics that remain constant during the analysis of the image has been included to improve the performance of the method; on the one hand, the CV or coefficient of variation[36-38] that indicates how scattered are the magnitudes of the data in the image and the average of the minimums of each row of RGB image that gives us information about the type of skin. The feature extractions are applied to every image, and the method is shown in Figure 6, on the other hand, Figure 7 shows the general architecture of the MLP network.

Training of multilayer perceptron

From the 20 photographs we obtained a total of 2,182,206 (number of pixels of the total images) input patterns, and 2, 182, 206 desired outputs. Whereas, each input pattern P is formed by 5 features, the 3 RGB components of each pixel of the original image; plus, the mean of the minimums and the variation coefficient of the photograph. To obtain the desired output T, each photograph has been binarized manually with the help of dermatologists, thus the value of 0 has been assigned to the pixels corresponding healthy skin; and the value of 1 has been assigned to the pixels corresponding skin with vitiligo [Figure 6b]. In the end, each T pattern has two states only, 1 or 0; resulting the input pattern to be $P_{5 \times 2\ 182\ 206}$ and the desired output is $T_{1 \times 2\ 182\ 206}$.

Of all the obtained data, 70% was used for training, 15% for cross-validation and the remaining 15% for the evaluation of the generalization and learning of the MLP. Because there is no analytical method to determine the number of neurons in the hidden layer,[31] several tests were performed modifying the number of neurons in the hidden layer. During the training test, 10,000 epochs were used. The smallest error was reached in the 9941 period with a mean square error of 0.1468, both for validation and for testing. The best result was obtained by using 12 neurons in the hidden layer.

Experimentation

To evaluate the performance of the proposed method (MLP) to detect areas of repigmentation in the skin, pattern images were constructed. To do this, samples of the skin color (healthy and with vitiligo) of different patients were selected. It should be noted that the images used in the experimentation are not the same as those used during the training of the MLP network.

The characteristics of the pattern images were selected using an orthogonality based experiment (experiments are organized in an orthogonal table optimally and statistics are applied to analyze their results, the design consists of: Determine the objective of the experiment, determine the experimental factors and define their level, choose the exact form of the orthogonal table and finally place all the previous parameters within the table).[39] Based on these, two experiments were developed. In the first experiment, eight pattern images using modeled skin (Gaussian distribution was used to model healthy skin and skin with vitiligo) were constructed [Figure 8] where: Skin type (based on the Fitzpatrick scale), the amount of skin with vitiligo, and the amount of repigmented skin that may exist in an image were selected as independent variables. On the other hand, in the second experiment, 12 pattern images were constructed [Figure 9], but using real skin where: six samples of six different patients were selected, two patients with skin Type II, two patients with skin Type III, one patient with skin Type II, and one patient with skin Type III, but additionally, there is body hair in both, the healthy skin and the skin with vitiligo, similarity to the first experiment skin type, the amount of skin with vitiligo, and the amount of repigmented skin that may exist in an image were selected as independent variables. The amount of affected skin and the type of skin color modeling was based on a similar study developed by Fadzil *et al*.[15] The scheme of the first and the second experiment are shown in Tables 1 and 2, respectively.

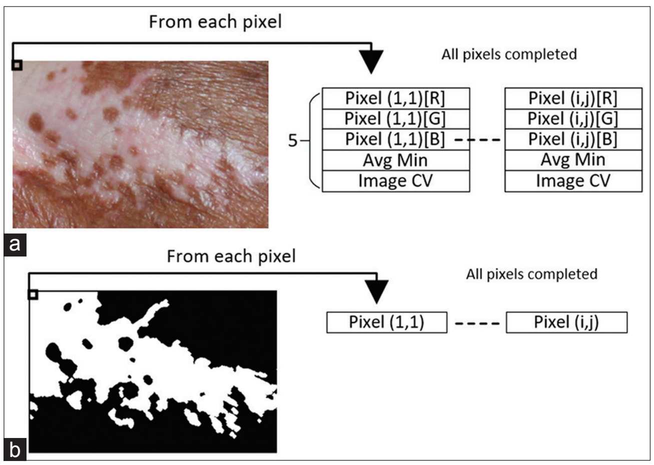

Figure 6: Featured extraction of images, (a) Input of multilayer perceptron. Featured extraction of images, (b) Desired Output

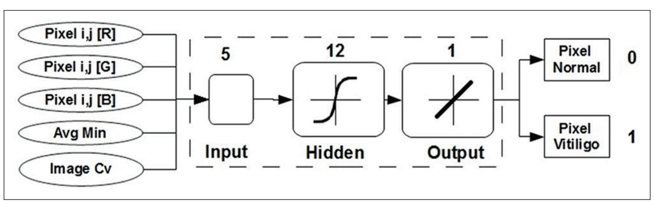

Figure 7: Proposed architecture of multilayer perceptron. It should be noticed that the proposed method analyze the image pixel to pixel

The performance of the method is measured based on the detection rate of healthy skin and skin with vitiligo. To do this, sensitivity (Eq. 3), specificity (Eq. 4), and the F1 Score (Eq. 5) are used as metrics (it indicates the accuracy of a method with respect to its sensitivity and precision). In the case of the F1-Score, a value of 1 equals 100% accuracy, this value can be calculated using:

$$\text{Sensitivy} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{4}$$

$$F1-\text{Score} = \frac{2TP}{2TP+FP+FN} \tag{5}$$

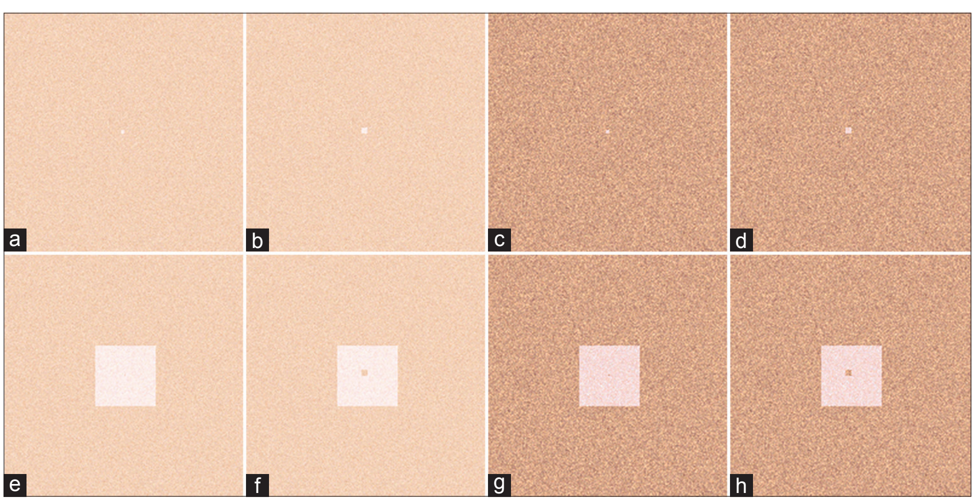

Figure 8: Pattern images constructed based on Table 1: (a-h) Test 1–7. It can be noticed that is a modeled skin

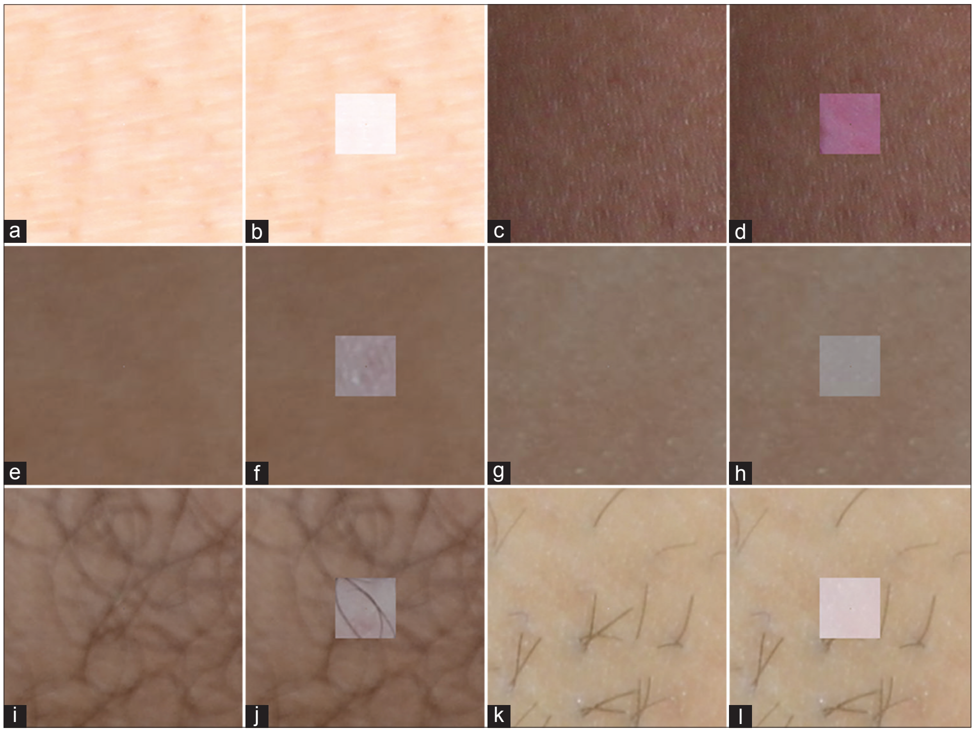

Figure 9: Pattern images constructed based on Table 2: (a) Test 9, (b) test 10, (c) test 11, (d) test 12, (e) test 13, (f) test 14, (g) test 15, (h) test 16, (i) test 17, (j) test 18, (k) test 17, (l) test 17

Table 1: Scheme of the first experiment using modeled skin

Test	Skin type	Repigmentation skin area	Affected skin	Resolution (pixels)
Test 1	Type II	0×0	1×1	200×200
Test 2	Type II	0×0	5×5	200×200
Test 3	Type III	0×0	1×1	200×200
Test 4	Type III	0×0	5×5	200×200
Test 5	Type II	1×1	50×50	200×200
Test 6	Type II	5×5	50×50	200×200
Test 7	Type III	1×1	50×50	200×200
Test 8	Type III	5×5	50×50	200×200

Table 2: Scheme of the second experiment using real samples

Test	Patient	Repigmentation skin area	Affected skin	Resolution (pixels)
Test 9	1	0×0	1×1	200×200
Test 10	1	1×1	50×50	200×200
Test 11	2	0×0	1×1	200×200
Test 12	2	1×1	50×50	200×200
Test 13	3	0×0	1×1	200×200
Test 14	3	1×1	50×50	200×200
Test 15	4	0×0	1×1	200×200
Test 16	4	1×1	50×50	200×200
Test 17	5	0×0	1×1	200×200
Test 18	5	1×1	50×50	200×200
Test 19	6	0×0	1×1	200×200
Test 20	6	1×1	50×50	200×200

Where TP (true positives) represent the skin pixels with vitiligo correctly detected, FP (false positive) represents the healthy skin pixels detected as skin with vitiligo, and FN (false negative) represents the skin pixels with vitiligo detected as healthy skin. In addition, two similar work methods were used (method based on ICA[15] and method based on FCM[17]) to compare their results with respect to the proposed method.

Results and Discussion

Table 3 shows the results of the methods in the first experiment. In the first four tests (Test 1 to Test 4), what is sought is to evaluate the performance of the methods to identify areas of depigmentation that correspond to skin affected with vitiligo.

The results indicate that the proposed method and the ICA method are both capable of correctly detecting the pixels that either correspond to healthy skin or skin with vitiligo. In the first four tests, the three methods obtained a score of 100% with respect to their sensitivity, with the exception of the test 4, where the ICA method achieved 96% of sensitivity. With respect to its specificity, in Test 1 and Test 2, the method of ICA obtained better results than the proposed method, however, said proposed method also obtained a good result as it reached 99.62% for both tests; that is to say with regard to the method of ICA a difference of 0.35% and 0.04%, respectively. On the other hand, in Tests 3 and 4, the proposed method was the better score obtained from the three applied methods; as in being 100%

Table 3: Results of the first experiment using modeled skin samples

Test	Method	Sensitivity (%)	Specificity (%)	F1-score
Test 1	ICA	100	99.97	0.6000
	FCM	100	51.14	0.0009
	MLP	100	99.62	0.1058
Test 2	ICA	100	99.66	0.2674
	FCM	100	51.14	0.0026
	MLP	100	99.62	0.2475
Test 3	ICA	100	99.99	0.9000
	FCM	100	48.71	0.0009
	MLP	100	100	1
Test 4	ICA	96.00	100	0.9796
	FCM	100	48.72	0.0024
	MLP	100	100	1
Test 5	ICA	96.28	99.74	0.9769
	FCM	100	99.04	0.9326
	MLP	99.96	99.61	0.9713
Test 6	ICA	99.96	97.92	0.8634
	FCM	100	99.06	0.9336
	MLP	99.96	99.63	0.9726
Test 7	ICA	99.64	99.87	0.9883
	FCM	100	99.85	0.9885
	MLP	99.80	99.98	0.9974
Test 8	ICA	99.11	99.99	0.9945
	FCM	100	99.87	0.9900
	MLP	99.80	100	0.9990

ICA – Independent component analysis; FCM – Fuzzy C-Mean; MLP – Multilayer perceptron type

accuracy to detect the pixels of healthy skin and skin with vitiligo.

It should be noted that the low results obtained in the F1-score were due to the fact that there is a single value (1 pixel) corresponding to a true positive so that when said method detects a false positive or false negative, it greatly diminishes the score on this metric and not necessary shows low performance. If the scores obtained by both methods are to be observed, these are very acceptable (around 99% accuracy); however, due to the false positives and false negatives detected their F1-score value is low. The FCM method did not obtain good results in any of the cases, being that in its best test it obtained a result of 51.14% of specificity. Its low performance in these tests was due to the fact that being a clustering algorithm it divides the photo into two groups, in this case, having been only one (1 × 1) or 25 (5 × 5) pixels that contain skin with vitiligo, the algorithm did not consider them to be a reference in any of two groups (healthy skin and skin with vitiligo). The results of the three methods subjected to Test 1 are shown in Figure 10, from which it can be noticed the low performance of the FCM method in contrast with the results of other methods.

The following tests (Test 5–Test 8) look to evaluate the performance of the methods to detect correctly an area of

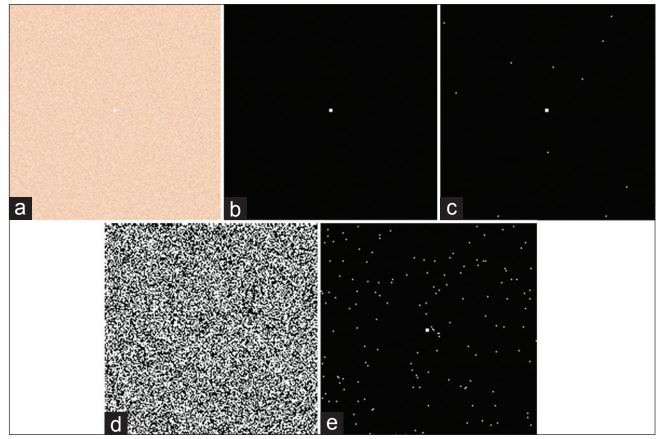

Figure 10: Responses of the three methods to the test 1: (a) Pattern image, (b) desired response, (c) independent component analysis method, (d) Fuzzy C-Means method, (e) proposed method

repigmentation that could exist in an area affected with vitiligo, and simultaneously its accuracy to detect healthy skin and skin with vitiligo as such. For these tests, the three methods obtained quite similar results; furthermore, the FCM method was capable of identifying each type of skin due to the fact that the area with affected skin was greater in the first tests, allowing it to identify the pixels that corresponded to each type of skin.

The F1-Score allows us to have a general vision of the accuracy of a determined method, in these tests the amount of true positives are significant (around 2500) with respect to the FP and FN of the image; and thereby the metric of the F1-score may be valid to give a benchmark of performance of the methods. Based on this parameter, among these tests, the proposed method was the most accurate being that it obtained the highest F1-score; obtaining an average of the 4 tests, an F1-Score of 0.9851 while the ICA method and the FCM method achieved an F1-score of 0.9558 and 0.9612, respectively. In some of the tests, the proposed method did not obtain the best result in regards to its sensitivity or its specificity but obtain the highest score in the F1-Score. This fact must be considered for future references due to the false positives in tests could be confused as skin with vitiligo, and thus show a greater area of skin as being affected than what in reality is. The results of the three methods in Test 8 are shown in Figure 11, from which it can be noticed that methods detect correctly the skin with vitiligo but also some false positives.

Table 4 shows the results of the methods in the second experiment, using real skin samples. It should be noted that some areas of the skin of certain individuals, it tends to generate a shine peculiar of each person and skin type being that in these cases the proposed method and the other methods confuse this shine as skin with vitiligo. In the test where only exist one pixel with vitiligo the FCM method still not obtain good results, similar to the results in the first experiment in this kind of pattern images.

It can be noted that the proposed method and the ICA method detect various false positives (could be caused by shine skin) but it also detects correctly the 1 pixel corresponding to skin with vitiligo. Although FP and FN were detected in some tests, the proposed method obtained the best results in contrast to the other tested methods and due to in this tests are using real skin the proposed method shows potential to be used in clinical applications. This fact can be observed in Figure 12 (the results of the methods in the Test 9 is shown).

The last four tests (Test 17–Test 20), has the particularity that the real skin samples contain healthy skin, skin with vitiligo an also body hair. The FCM method incorrectly detects lots of pixels, that is, the fact of its lower metrics in Table 4. However, It is interesting to noted that the presence of body hair not affect significantly the response of the proposed method and the ICA method, though the proposed method obtained better results, except in the test 20; in this test due to the characteristic of the skin some areas has a kind of brightness causing the false positive detection. Figure 13 shows the results of the methods in the test 20, where can be observed the mentioned above.

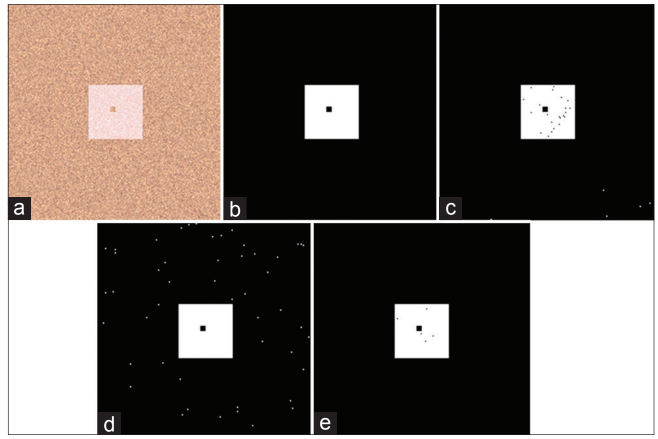

Figure 11: Responses of the three methods to the test 8: (a) Pattern image, (b) desired response, (c) independent component analysis method, (d) Fuzzy C-Means method, (e) proposed method

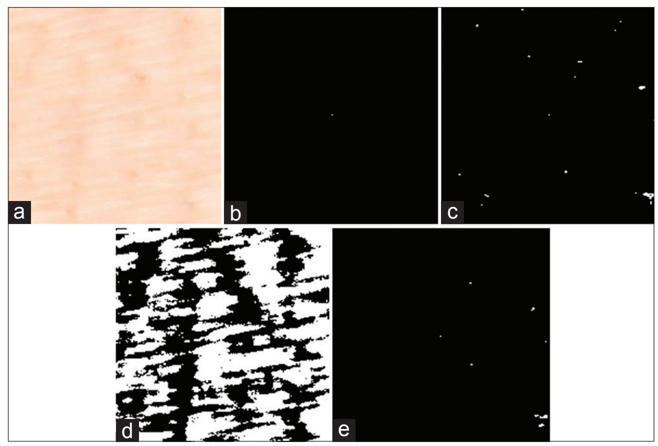

Figure 12: Responses of the three methods to the test 9: (a) Pattern image, (b) desired response, (c) independent component analysis method, (d) Fuzzy C-Means method, (e) proposed method

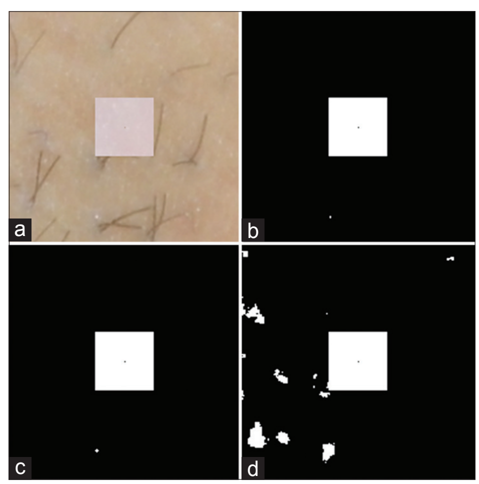

Figure 13: Responses of the three methods to the test 20: (a) pattern image, (b) independent component analysis method, (c) Fuzzy C-Means method, (d) proposed method

Conclusion

In this paper, an MLP and the characteristics of the light interaction with the skin were used to determine the pixels corresponding to healthy skin and skin with vitiligo from an RGB image. Its results were contrasted with two methods of similar works. It is noteworthy that the tests tried to simulate different scenarios that could happen in a real case.

We analyze the result of the methods based on three parameters (sensitivity, specificity, and F1-Score) to have a global vision of their performance. The proposed method demonstrated the best performance of the three methods, and it also showed its capability to detect healthy skin and skin with vitiligo in areas up to 1 × 1 pixels. In tests with real skin, the proposed method detected various false positives; however, among all the methods, it obtained the best possible results. In the pattern images that contain body hair, it can be observed that the proposed method has a good response according to the other methods, to different conditions of the skin of the skin, in this kind of images, the body hair did not represent problems, but areas on the skin that reflect too much brightness in the photograph is a factor to consider due to could be a limit in any method that uses images. However, related to clinical applications the proposed method present several advantages based on the obtained results. It should be noted that some photographs could have very thick body hair, in this case, the proposed method could not respond accurately, but this could be due to the thickness of the body hair that could be covered the skin by them resulting in an erroneous response. The relevance of this method lies in the fact that ANNs only require huge computational cost during its training; being that a trained network could be easily used in mobile health, and if it is required, the performance of the proposed method would be significantly improved by increasing the training patterns. The next step in our research, considering the problems due to shine (detecting

Table 4: Results of the second experiment using real skin samples

Test	Method	Sensitivity (%)	Specificity (%)	F1-score
Test 9	ICA	100	99.80	0.0247
	FCM	100	47.76	0.0001
	MLP	100	99.90	0.0476
Test 10	ICA	100	97.31	0.8323
	FCM	100	99.97	0.9980
	MLP	100	99.86	0.9897
Test 11	ICA	100	99.29	0.0069
	FCM	100	50.03	0.0001
	MLP	100	99.67	0.0148
Test 12	ICA	100	0.9931	0.9507
	FCM	98.88	99.59	0.9650
	MLP	98.08	100	0.9903
Test 13	ICA	100	100	1
	FCM	100	61.10	0.0001
	MLP	100	100	1
Test 14	ICA	100	98.59	0.9046
	FCM	100	100	1
	MLP	100	100	1
Test 15	ICA	100	100	1
	FCM	100	51.70	0.0001
	MLP	100	100	1
Test 16	ICA	100	99.98	0.9986
	FCM	100	99.99	0.9994
	MLP	100	100	1
Test 17	ICA	100	95.94	0.0012
	FCM	100	49.79	0.0001
	MLP	100	96.43	0.0014
Test 18	ICA	99.92	84.90	0.4686
	FCM	99.44	67.70	0.2907
	MLP	100	99.62	0.9722
Test 19	ICA	100	97.26	0.0019
	FCM	100	34.54	0.0001
	MLP	100	98.32	0.0030
Test 20	ICA	100	99.99	0.9996
	FCM	100	99.98	0.9990
	MLP	100	97.855	0.8608

ICA – Independent component analysis; FCM – Fuzzy C-Mean; MLP – Multilayer perceptron type

false positives) and thick body hair, will be to develop a method based on machine learning algorithms that are robust to the brightness that may exist on the skin and it can be consider the use of a preprocessing technique to remove the thick body hair, if its required.

Providing the physicians and patients an objective method to evaluated pigmentary disorders such as vitiligo will help doctors and patients to make smarter and faster decisions during the evaluation process, helping to decreases the stress caused by the lengthy treatment of patients.

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Conflicts of interest

There are no conflicts of interest.

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