Intelligent machine learning algorithms for colour segmentation

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Abstract: - Skin colour detection has been a commendable technique due to its wide range of application in both analyses based on diagnostic and human computer interactions. Various problems could be solved by simply providing an appropriate method for pixel-like skin parts. Presented in this study is a colour segmentation algorithm that works directly in RGB colour space without converting the colour space. Genfis function as explored in this study formed the Sugeno fuzzy network and utilizing Fuzzy C-Mean (FCM) clustering rule, clustered the data and for each cluster/class a rule is generated. Also, the Radial Basis Function (RBF) utilized Gaussian function for grouping. Finally, corresponding output from data mapping of pseudo-polynomial is obtained from input dataset to the adaptive neuro fuzzy inference system (ANFIS), while the Euclidean distance performed data mapping in the RBF model. The result obtained from these two algorithms depicts the RBFN outperforming ANFIS with remarkable margins.

Key-Words: - **S**kin, nonskin, adaptive neuro fuzzy inference system, radial basis function.

1 Introduction

The skin is seen as one of the most distinguished and unique features of humans. In several fields, skin detection has applications including identity confirmation and identification based on military and security applications, facial characteristics, camera remote control, video conferences, skin tracking in video, information access, managing pictorial information in banks and so on. This paper explores ANFIS algorithm to detecting skin from nonskin instances. Fuzzy neural networks and systems are generally known estimators that estimates any given non-linear function with intended accuracy under the condition of the presence of sufficient neurons in the middle layer and fuzzy rules. Recent studies in the field of fuzzy systems and neural networks indicate that the combination of these two methods can be very effective in nonlinear systems identification.

ANFIS structure works by integrating adaptive neural networks and fuzzy logic parameters which can be set based on the input and output data to model the systems [1]. The basic principle used in training the adaptive networks is the rule of reducing gradient. Using gradient reduction alone is not desirable due to the slowness and tendency of the local minima to set network parameters. However new hybrid methods that are the result of combining gradient reduction and other similar methods lead to increased speed of least square error (LSE). Fuzzy modeling and detection was earlier analyzed by Takagi-Sugeno and obtained practical applications in the field of control, detection and prediction. Adaptive neuro fuzzy inference systems works by combining fuzzy structures with artificial neural networks that are used to detect systems, predict time series and other various cases. There is a high level of uncertainty to achieve the desired automatic segmentation in each image segmentation layout. This fact also can be extended into face detection especially skin color segmentation. Therefore, fuzzy theory is a good way to achieve the basic detection because fuzzy model provides a mechanism that presents image uncertainty. According to the fuzzy rules extracted from different color spaces used in training phase, each pixel can be divided into the skin or non-skin pixels. One of the features of pixels-based color is that it required no space ground, therefore fixed and fast orientation and size for processing, detection and tracking applications such as detection of specified body parts of human, nudity detection and detection of face; all of which benefits from skin detection. Moreover, detection of skin color helps to block the abusive image or video content. In addition to its use in computing, color of human skin color plays a vital role in human and human relationships.

Dealing with black and white colors does not provide any satisfaction with image. Projecting the degree of membership is a new way to solve the problems and issues to deal with vague fuzzy data or in a fuzzy form through which the fuzzy systems are allowed to control certain random levels without causing damage and endangering performance to the system. Fuzzy neural system is one of the most tangible and most successful aspects of this effort.

Linking and fuzzy neural system integration could be performed in two ways: a fuzzy system augmented by a neural network to promote some of its features such as speed, flexibility and the ability to adapt known as neural-fuzzy system NFS or ANFIS an equipped neural network with the ability to handle and control fuzzy information (fuzzy neural network). The design of adaptive neural-fuzzy system is orchestrated to induce the fuzzy reasoning processes where network connections are consistent with the parameters of fuzzy reasoning. Using fuzzy clustering for color image segmentation [2] is one of the methods of segmentation based on pixels, where the fuzzy system determines each pixel belongs to which category. Therefore, the purpose is to create a fuzzy system that can classify more colors. To do so, an expert is required to sets the rules and membership functions according to the training data which is very time-consuming and cumbersome and the final rules might not be the best ones. Therefore an automatic method is required to create fuzzy rules and membership functions according to the training data. Many techniques have been developed for this purpose. In this article ANFIS method has been devised to produce membership functions and fuzzy rules automatically. The main advantage which provides explicit meaning for skin models is their simple decision making rules and integrating them with the main advantages of nonparametric skin models that is; having lower decision making time for training and clustering. In order to perform this method a fuzzy model for detecting skin in color images is presented.

2 Related Studies

The three primary colors corresponding to RGB are: red, green and blue, respectively. The RGB color components are normalized to reduce the dependence on lighting so that, sum of the normalized components is unity i.e $r + g + b = 1$. The third component does not hold any significant information since the sum of these components is 1 and is normally dropped for dimensionality reduction purposes. Under certain assumptions, it is observed that the differences the skin-color clusters in RGB space have relatively lower variance than the corresponding clusters in RGB therefore, are demonstrated to be useful for detection and modeling of skin color [3, 4]. Regarding the advantages mentioned above, a popular choice for detection of skin is the RGB and has been utilized by Brown et al. [5], Oliver et al. [6], Caetano and Barone [7], Bergasa et al. [8], Kim et al. [9], Sebe et al. [10], Soriano et al. [11], Schwerdt and Crowley [12], Wang and Sung [13], Storring et al. [14], Yang and Ahuja [3], Iraji [15] and Yang et al. [4]. Commission Internationale de l'Eclairage (CIE) system describes a luminance component Y as color, and other two components X and Z. The values of CIE–XYZ were constructed from psychophysical experiments and correspond to the color matching characteristics of human visual system. It is confirmed that Chen and Chiang [16], Brown et al. [5] and Wu et al. [17] used this color space. As described by Lior Shamir [18], a human perception based approach is linked to segmentation of pixel color. The H, S and V components defines fuzzy sets of the HSV color space and generate a model of fuzzy logic that aims to follow the classification of color based on human intuition. Simple modification of the classification by knowledge-driven model based on needs of a specific application and the efficiency of the algorithm in terms of the computational complexity makes the proposed method suitable for applications where efficiency is a primary issue. M. Hamidi and A. Borji [19] using fuzzy logic, have proposed a new method for color image segmentation where they automatically produce a system for classification of color and segmentation of image with minimum error rate and least number of rules. To find optimal membership functions and fuzzy rules, a comprehensive learning particle swarm optimization technique is used as it discourages premature convergence. Compared to other approaches such as ANFIS, less computational load is needed when using this method. Variety of large train data set makes the proposed algorithm invariant to noise illumination.

Rajen Bhatt, Abhinav Dhall, IIT Delhi first compiled this dataset in 2009 [20] where they published a paper titled "efficient skin region segmentation using low complexity fuzzy decision tree model" in the Indian IEEE conference known as INDICO1. Same researchers published a paper titled "adaptive digital makeup" in the same year in the international symposium on visual computing (ISVC). Leonid Sigal et al. [21] in real time systems and video conferences put forward a novel method for skin segmentation. Despite the great variety of skin types this segmentation enjoyed a fairly reliable performance. Even in brightness changes, this approach was effective. Furthermore, the Markov's method is used in this study [22]. An algorithm for segmentation of skin region in color images using edge and color information was presented by Bouzerdoum. Historically, the skin color regions were used for detection of human skin color using

Bayesian model [23]. Considering high processing speed, Rodrigo Verschae et al. performed segmentation of skin regions by examining the closest pixels [24]. A new method to solving the segmentation of skin problem was designed by Junwei Han et al. [25]. At first, given a gesture of video sequences, a g eneral skin model was developed. The data were automatically gathered from several frames. Conclusively, an SVM classifier was utilized for the detection of skin pixel on active learning basis [25]. In [26], Mohammad Shoyaib et al. performed detection of skin utilizing color distance map. Moreover, a novel recognition technique of the face was introduced; a hybrid of main components analysis and skin color segmentation known as SCS-PCA [27]. In [28], K. K. Bhoyar et al. used a classification method known as novel neural network symmetric to detect pixels of skin from non-skin ones in color images. Methods of data mining such as k-means were as well utilized for detection of skin and worthwhile results were obtained as demonstrated in [29]. In this study [29], Hamid A. Jalab using a cluster pixel model designed segmentation of skin under specifiable environmental conditions. This proposed model can overcome the changes in complex backgrounds and sensitivity to brightness conditions [30]. In [31], P. Kakumanu et al. presented modeling and detection of skin and this is recommended for further study. In conclusion, associated with the current issue, the most outstanding results is obtained using fuzzy system combined with support vector machine (FS-FCSVM) [32].

3 Proposed Algorithms

In this paper, we explored and compared the performances of Adaptive Neuro Fuzzy Inference System (ANFIS), Radial Basis Fuction Network (RBFN) to properly recommend the best performing network to dermatologists for skin.

3.1 Skin detection using ANFIS

Adaptive Neuro Fuzzy Inference Systems (ANFISs) as explored in this paper is a r ule and knowledge based system. ANFIS focal point is the knowledge base that is made up of the if-then fuzzy rules. Convincingly, if-then expression is simply the if-then fuzzy rules which are specified by a continuous membership function [33, 34]. In this paper, we explored ANFIS algorithm. An algorithm is the basic component of any intelligent system. An algorithm processes and generates knowledge from data [35, 36, 37]. Creating systematic algorithmic models encompasses many steps. The first step is data preprocessing which is an important step in data mining; it filters and makes data ready for operations. Analyzing unfiltered data can generate inappropriate model or misleading results. Hence, the representation and quality of data is first and foremost before further analysis and classification. The second step as featured in this paper is feeding the processed data onto the classifier; ANFIS models.

This section proposed an intelligent ANFIS for detection of skin from nonskin. This proposed algorithm is capable of detecting skin by taking mixture of RGB color space of both skin and nonskin pixels. The design stages of ANFIS are studied and implemented in this section. Beginning with the dataset, the data matrix with dimensions utilized by the algorithm is of 4*245057 (four columns and 245057 rows) where the first three columns represents R, G, and B i.e X1, X2, and X3 features and the fourth column represents the class labels; 1 for skin and 2 for non-skin. Here, detection of skin from nonskin is carried out by introducing the three R, G, and B components onto the model. Considering the extremely large number of rows, the holdout cross validation technique was explored to randomly sample the dataset into training and test sets, to minimize the biasness of the model. For high performance accuracy to be obtained, the dataset were normalized/rescaled to the range of [0, 1]. For higher system flexibility, MATLAB R2015a was used for designing and implementing the ANFISs. Figure 1 be low demonstrates the framework flowchart.

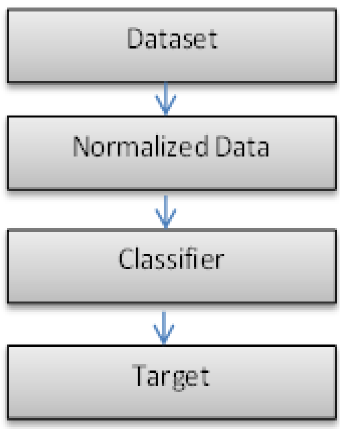

Fig. 1, Flowchart of the framework

The ANFIS morphology used in this study is made up of five layers of nodes from which the first and the fourth layers composed of the adaptive nodes having defuzzification and fuzzification incorporated, while the second, third and fifth layers comprise of fixed nodes with rule, neuron summation and normalization incorporated. Moreover, in subsequent iterations, the adaptive nodes are linked with their respective parameters constantly updating each node, and all other parameters are devoid by the fixed nodes. Architecture of the ANFIS was built on two fuzzy if-then rules using the first order Sugeno model as also demonstrated in [38-40].

First Rule: If (x is A_1) and (y is B_1) then (f_1 = p1x + q1y + r1)

Second Rule: If (x is A_2) and (y is B_2) then (f_2 = p2x + q2y + r2)

From the above two fuzzy rules, X and Y are predefined membership functions, B_i and A_i are membership values, q_i, p_i, and r_i are consequent parameters constantly updated in the forward pass in the learning algorithm and finally, f_i are the outputs. The implemented ANFIS architecture displaying those two fuzzy rules is depicted in Figure 2 where a square represents an adaptive node and a circle represents a fixed node.

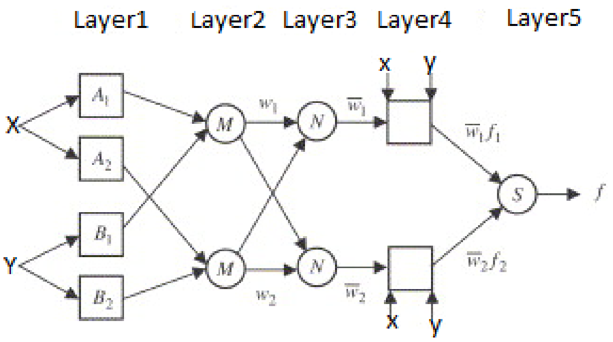

Fig. 2, Architecture of the ANFIS

From the above ANFIS structure,

- Layer 1 represents the fuzzification layer where every node i in the layer is an adaptive node. Outputs of this layer represents the fuzzy membership grade of the inputs given by:

$$O_i^1 = \mu A_i(x), for\ i = 1,2 \qquad (1)$$

$$O_i^1 \mu B_{i-2}\,(y), for\ i = 3,4 \qquad (2)$$

Where y and x are the inputs to node i, A is a linguistic label; small, large and $\mu_{Ai}(x)$, μ_{Bi}-$_2(y)$ assumes all fuzzy membership function.

$\mu_{Ai}(x)$ was chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0, so that:

$$\mu A_i(x) \ = {}^{1}\!/_{1} \ + \left\{(x - \frac{ci}{a_i})^2\right\} b \qquad (3)$$

From equation 3, a_i, b_i and c_i represent the membership function parameters. Here, parameters are referred to as premise parameters.

- Layer 2 represents rule layer having a fixed node whose output is the product of all the incoming signals. Layer 2 output is depicted thus:

$$O_i^2 = w_i \ = \ \mu A_i(x)\ \mu B_i \ (y) i = 1,2 \qquad (4)$$

- Layer 3 represents the normalization layer having a fixed node represented by circle node:

$$O_i^3 \ = \ w_i = \frac{w_i}{(w1 + w2)i} = 1,2 \qquad (5)$$

- Layer 4 represents the defuzzification layer having an adaptive node. Each node's output in this layer is simply a first order polynomial and the product of the normalized firing strength as shown in equation 6:

$$O_i^4 = w_i f_i \ = \ w_i(p_i x + q_i y + \ r_i) i \ = 1,2 \quad (6)$$

- Layer 5 represents the Summation neuron having a fixed node computing the overall output as the summation of all incoming signals as demonstrated below:

$$O_i^5 = \sum 2\, w_i\, f_i = \sum 2\ i = 1 w_i f_i / \,(w1 + w2)(7)$$

This Hybrid technique; neuro-fuzzy brings learning capabilities of neural networks to fuzzy inference systems. Where the membership functions of the Sugeno-type fuzzy inference system are fine-tuned by the learning algorithm using the training input and output data, checking input and output data; to minimizing over-fitting and finally a back propagation algorithm in combination with a least squares type of method. The proposed ANFIS classifier is presented as dermatologist's diagnostic tool in analyzing human skin as well as identifying skin from nonskin. It uses a hybrid approach of adaptive neuro-fuzzy inference system comprising two intelligent techniques; neural network (NN) and fuzzy inference system (FIS) to obtaining good reasoning in quantity and quality. That is, it is programed using NN and Fuzzy reasoning calculations.

In this section of our study, the classification objective is to classify skin from nonskin in a given dataset. The feature vectors extracted from RGB colour space were used as the input to the ANFIS model. Afterwards, a smaller number of iteration steps were converged using ANFIS; the hybrid learning algorithm. As depicted in figure 2, implementation of the ANFIS networks has a total of 8 fuzzy rules for experiment 1, 27 fuzzy rules for experiment 2 and 1 target for the two experiments. The ANFIS classifiers used Gbell membership functions (MFs). Choice of membership function selection is basically dependent on the user's application since there is no rule/regulation in choosing them. Here, the general ideal would be to use minimum training parameters to generate the best smallest error measure. Accepted error measure virtually determines the number of epochs fixed by the user. In this paper, 100 epochs was fixed for Experiment 1 and 2. First and second experiments resulted to 89.40% and 90.10% respectively. Results of the proposed experimental models are extensively depicted in table 1.

Table 1, Experimental results

Learning Parameters	Experiment 1	Experiment 2
Number of extracted feature vectors (model input)	3	3
Epochs	100	100
Number of fuzzy rules	8	27
RMSE	0.38	0.34
Recognition rate	89.40%	90.10%

Table 1 above demonstrates the experimental results. In both experiments, every other parameter was left constant except number of fuzzy rules. In Experiment 2, the number of fuzzy rules was increased from 8 to 27 and this raised the recognition rate from 89.40% to 90.10%. The result of these experiments generates a conventional rule; increase in the number of fuzzy rules increases the performance of the ANFIS technique. Figure 3 depict error tolerance curve for Experiment 2 (model having the best performance accuracy).

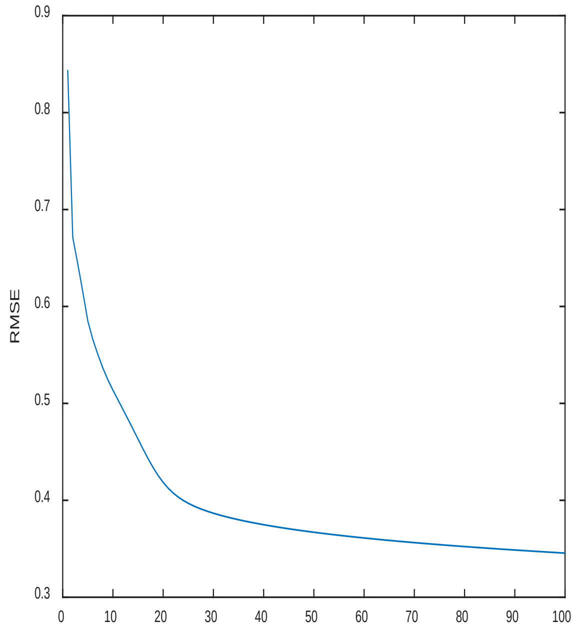

Fig. 5, RMSE learning curve

3.2 Radial basis function networks (RBFNs) for skin detection

RBFN is a peculier kind of neural system. In the most part, when people talk about mimicked neural networks or neural networks, they are implying the multilayer perceptron (MLP). In a MLP, each neuron takes the weighted aggregate of its data esteems. That is, each of the information regard is expanded by a coefficient, and the results are summed. A single MLP neuron is a clear straight classifier; however complex non-direct classifiers can be worked by merging these neurons into a network [41].

Generally, the approach in RBFN is more natural than that of the MLP. A RBFN performs gathering by measuring the information's closeness to cases from the readiness set. Each RBFN neuron stores a "model", which is just a single of the cases from the arrangement set. When we have to orchestrate data, each neuron forms the methodical detachment between the data and its model. Also, if the data happens to resembles class A models than the class B models, it is named class A. This is shown in figure 6 below.

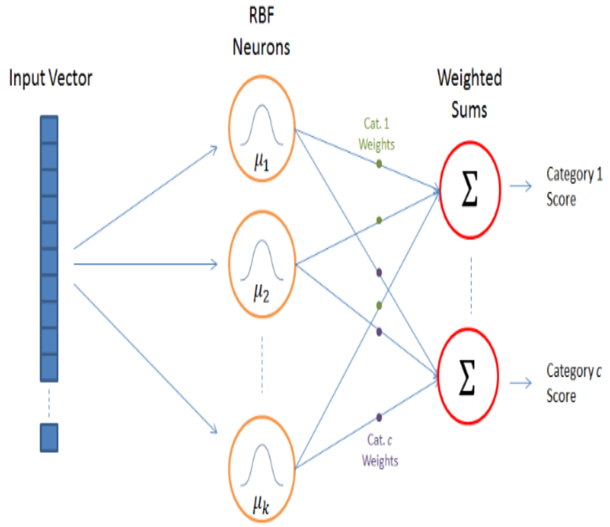

Fig. 6, RBF Network architecture

The above delineation demonstrates the common engineering of a RBFN model. It comprises of input vector, an RBF neurons layer and a t arget layer having a node for each classification or group of data.

Satisfactorily, the n-dimensional vector is the input vector in which attempt is made to classified. The whole input vector is appeared to each neurons of the RBFN.

In our proposed RBF classifier, each neuron of the classifier stores a "model" vector which is only one of the vectors from the preparation group. Each neuron of the RBF looks at the input vector to its model, and outputs an incentive in the vicinity of 0 and 1 which is a measure of closeness. On the off chance that the input is equivalent to the model, then the neuron of the model output would be 1. When the separation between the input and model develops, the reaction exponentially tumbles off towards 0. The state of neuron of the RBF's reaction is a chime bend, as outlined in the network design chart.

The peak reaction of the neuron is additionally called its "actuation" score. The model vector is additionally frequently known as neuron's "middle", for it is the incentive at the focal point of the chime bend.

The output of the network comprises of an arrangement of nodes, one for each classification that we are attempting to be classified. Every node at the output layer processes a kind of score for the related classification. Regularly, the choice of theclassification is made by mapping out the input to the class with the most outstanding score.

The score is prepared by taking a weighted sum of the established figures from every neuron of the RBF. By weighted sum we suggest that a t arget node relates a weight in motivation with each of the neurons in RBF, and copies the neuron's order by this weight before adding it to the total response.

Since each target node is figuring the score for an alternate classification, each node at the target layer has its own specific weights course of action. The output of the node would conventionally give a positive weight to the neurons of the RBF that have a place with its classification, and a negative weight to the others.

RBFN networks are very much related to back propagation networks topology. Basic irregularities are in the analogy behind weight computation. The activation function used at the neurons' outputs basically has one hidden layer. The hidden layers with regards to a neural system give a g roup of "criterions" (radial-basis functions) constituting arbitrarily the "basis" for input designs when they are ventured into hidden layer. [42].

The motivation behind RBFN and some other neural network classifiers is based on the knowledge that pattern transformed to a higher-dimensional space which is nonlinear is probably more to be linearly separable compare to that in the low-dimensional vector representations of same patterns (cover's separable theorem on patterns). The output of neuron units are calculated using k-means clustering similar algorithms, after which Gaussian function is applied to provide the unit final output. In the training phase, the hidden layer neurons are usually centered randomly in space on subsets or all of the training patterns space (dimensionality is of the training pattern) [43]. After this, the Euclidean distance between each neuron and training pattern vectors are calculated, then the RBF (also referred to as a kernel) applied to calculated distances. Since the radius distance is the focal point to the function, hence the name; radial basis function [44] as shown in equation 8

$$Weight = RBFN\ (distance) \tag{8}$$

Other functions such as logistic and thin-plate spline can be used in RBFN networks but in this paper, the Gaussian function was utilized to execute the grouping. In training, radius of Gaussian function is usually chosen and this affects the extent to which neurons influences the considered distance. The multiplication of both the output values summation of the RBFs and weights computed for each neuron leads to the best predicted value for the new point as shown in [43]. The equation relating Gaussian function output to the distance from data points (r>0) to neurons center is given by:

$$\varphi(\mathrm{r}) = e^{-r^2/2\sigma^2} \qquad (9)$$

Where, the smoothness of the interpolating function is controlled using σ [42] and r is the Euclidean distance from a neuron center to the training data position.

3.2.1 RBFN training phase

In order to obtain a stable and reliable result, three experiments were performed (RBFN1, RBFN2 and RBFN3) with different values of hidden neurons and spread constant trained on two different datasets; about 70% for training and about 30% for testing. This aims to observe the networks' performances when trained with different values of spread constant. Table 2 summarizes the training parameters of three RBFNs used in simulation.

Table 2, RBFNs training parameters

Network parameters	RBFN1	RBFN2	RBFN3
Training samples(%)	70	70	70
Number of hidden neurons	30	50	80
Spread constant	0.14	0.5	1.0
Maximum epochs	100	100	100
Training time (secs)	25	19	21
Mean Square Error	0.0330	0.0304	0.0329

From the three RBFN experiments performed, the least/lowest mean square error obtained was at epochs 100 in experiment 2 (RBFN2). Figure 7 demonstrate the learning curve of networks RBFN2.

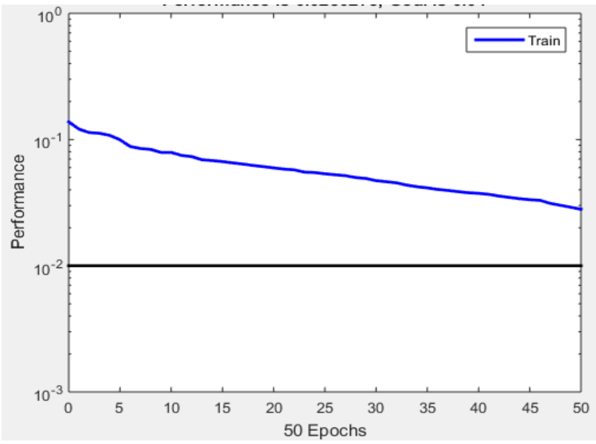

Fig. 7, RBFN2 learning curve

3.2.2 RBFN testing phase

Similarly, the Radial Basis Function networks (RBFN1, RBFN2 and RBFN3) were also tested using same configurations/parameters. The testing phase was assigned about 30% of the dataset. As shown in table 3, RBFN2 achieved the highest recognition rate (94.52%) amongst the three networks when tested on 30% of the data.

Table 3, RBFNs training and testing results

Network parameters	RBFN1	RBFN2	RBFN3
Training samples(%)	70	70	70
Test samples(%)	30	30	30
Detection rate	86.45%	94.52%	89.25%

The developed detection framework based on machine learning techniques (ANFIS and FBFN) are shown to be capable of detecting skin from nonskin. The explored networks in this paper demonstrated promising performances as d epicted in the simulation sections.

Best generalized detection accuracies obtained from the ANFIS and RBFNs are 90.10% and 94.52% respectively. It is remarked that the RBFN achieved higher recognition rate. That is, better generalization capability as compared to ANFIS. Moreover, the mean square error reached for the RBFNs after convergence were less than that of ANFISs.

4 Conclusion

In this study, we present an Adaptive Neuro Fuzzy Inference System and Radial Basis Function Network with very high potentials to detecting human skin from nonskin. Our proposed algorithms are capable of simulating human knowledge and experience from complex decision makings using approximate information and in environments with uncertainty. The explored approaches operate in accordance with particular characteristics for detecting human skin from nonskin. Considering the input data, detection using ANFIS is categorized as very low, low, median, and high. Regarding the obtained best results from the two algorithms, RBFN with 94.52% accuracy outperformed ANFIS having 90.10% accuracy. A dermatologist at the prestigious Near East University Hospital-Cyprus considered this result to be worthwhile. Interestingly, between the two ANFIS experiments; Experiment 1 having low fuzzy rules and Experiment 2 with high fuzzy rules, it was recorded that Experiment 1 having low fuzzy rules was outperformed by experiment 2 having high number of fuzzy rules. These two ANFIS experimental results show that the high number of fuzzy rules used in Experiment 2 actually boosted the performance of the system by increasing the performance accuracy by 0.7%. Observations from these experimental results proved that it is totally advisable to use moderately high number of fuzzy rules in ANFIS computation since further increase of the number of rules would result to reasonably high classification and performance accuracy. Furthermore, we are of no claim that our proposed systems have the best performances ever. To improve on the performance, future contributions to this problem would feature the repetition of the experiment using other machine learning techniques such as c o-adaptive neuro-fuzzy inference system (CANFIS), extreme learning machines (ELMs), deep learning and support vector machines (SVMs) to obtaining more optimal results.

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