USING AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) ALGORITHM FOR AUTOMATIC DIAGNOSIS OF SKIN CANCER

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Abstract
This paper presents a diagnosis system, based on an adaptive neuro-fuzzy inference system (ANFIS) algorithm, for applications in biomedical fields. This paper deals specifically with skin cancer diagnosis. Our system can be divided into two main parts: feature selection, using the Greedy feature flip algorithm (G-flip), and Classification method using ANFIS algorithm. The ANFIS algorithm could be trained with the back propagation gradient descent method in combination with the least squares method. Three different types of skin lesions were introduced to this diagnosis system and the performance of the ANFIS model was evaluated in terms of training performance and classification accuracies. The results confirmed that the proposed ANFIS model has potential in classifying the skin cancer diagnosis.

Keywords: ANFIS, Skin Cancer, Feature Selection, Greedy feature flip algorithm.

1 INTRODUCTION

The objective of this paper is to introduce ANFIS (Adaptive-Network-based Fuzzy Inference Systems) as a diagnosis system. ANFIS has proven to be an excellent function approximation tool, where it implements a first order Sugeno-style fuzzy system. The basic idea behind these neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modelling procedure to acquire information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system track the given input/output data. Researchers that worked with the same database by using Principal Component analysis (PCA) and Independent Component Analysis (ICA) (Mie et al., 2001), but their results on the discrimination between Actinikis Keratosis and Basal Cell Carcinoma were very poor, and therefore their conclusions about the fluorescence technique for discriminating these pathologies were very pessimistic.

The data inputs are features selected by the G-flip algorithm; from a number of features that were extracted from images of three different skin lesions (Fig. 1), are described in the next section. These images have been obtained by using the fluorescence technique from the Institute of Biophysics (University of Regensburg, Germany). These lesions can be classified into three groups: (1) Actinic Keratos or malignant melanoma, a type of skin cancer known also as a solar keratos, can be considered as the first step of the development of skin cancer). (2) Basal Cell Carcinoma is a cancer that begins in the deepest basal cell layer of the epidermis (the outer layer of the skin), and (3) Psoriasis is a chronic skin condition which tends to run in families. (David, 2003).

To avoid the presence of the large numbers of features we used the feature selection with the task of selecting a small subset of these features, sufficient to predict the target class well. Accordingly, a small good set of features could achieve a high performance level of classification even with using the most basic classifiers. Therefore feature selection is crucial for efficient learning.
Figure 1. Samples of fluorescence images of (a) Actinic Keratosis (b) Basal Cell Carcinoma, and (c) Psoriasis

The images shown were taken from different lesion groups and classes appear similar; they were transformed via several transfer functions which are considered as standard methods in image processing. The feature extraction involves first identifying features that discriminate among classes. In this study a comprehensive list of the features has been extracted and captured from different image treatment techniques in which specific characteristics of the images have been introduced.

2 FEATURE EXTRACTION

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. The features that were extracted in total 75 characteristics or parameters. In order to avoid highly redundant features we have extracted the correlation coefficient matrix and discarded those features with a correlation coefficient above 0.98 with respect to other features. In this way only 39 out of the initial 75 features have been selected. These features are extracted by using different algorithm of image processing: (1) Edge detection, with two main categories methods, Gradient and Laplacian. The Gradient method, mainly represented by three types (Sobel, Prewitt and Canny), (Odeh et al., 2006, Narendra and Fukunaga, 1977, Parker, 1997) detects the edges by looking for the maximum and minimum values that satisfy the first derivative of the image. The Laplacian method searches for zero crossings in the second derivative of the image to find edges. (2) Fourier transform, and (3) morphologic operations, where the dilation and erosion are considered as two fundamental morphological operations. More details about these features can be found in (Odeh et al., 2006)

These parameters have been extracted from database that contains 50 images of Actinidic Keratosis (pre-cancer), 50 images of Basal Cell Carcinoma (cancer) and 67 images of psoriasis.

3 FEATURE SELECTION

There is very large number of features, but only few of them are relevant for predicting the label. The feature selection is the task of choosing a small set out of a given set of features that capture the relevant properties of the data. The need for feature selection arises to avoid the presence of large number of weakly relevant and redundant features in the data set. A good choice of features is a key for building compact and accurate classifiers.

In this paper the Greedy feature flip (G-flip) (Gilad et al., 2004) algorithm is used to select a small set of features, that can be used as inputs to our diagnosis system.

G-flip is a greedy search algorithm for maximizing the evaluation function $e(F)$, where $F$ is a set of features. The algorithm repeatedly iterates over the feature set and updates the set of chosen features.
In each iteration it is decided to remove or add the current feature to the selected set by evaluating the margin term in the equation (1) with and without this feature. The following equation shows the evaluating function for a training set $S$ and a weight vector $w$ according to the second definition of the margin in (Gilad et al., 2004):

$$e(w) = \sum_{i=1}^{n} \Theta_{H_{i}}(x)$$

(1)

This algorithm converges to a local maximum of the evaluation function, as each step increases its value and the number of possible feature sets is finite. The computational complexity of one pass over all features of Gflip is

$$\Theta(N^2m^2)$$

(2)

where $N$ is the number of features and $m$ is the number of instances (Gilad et al., 2004). Empirically G-flip converges after a few iterations and there is no need to tune the number of features or any type of threshold.

4 CLASSIFICATION SCHEME

A modular classification algorithm based on the ANFIS has been used for this application. ANFIS applies two techniques in the updating features. For premise features that define membership functions, ANFIS employs gradient descent for fine-tuning purposes. For consequent parameters that define the coefficients of each output equations, ANFIS uses the least-squares method. This approach is called hybrid learning method since it combines gradient descent and the least-squares methods. (Ghomsheh, 2007)

In a fuzzy inference system, there are three types of input space partitioning: grid, tree, and scattering partitioning. The "curse of dimensionality" refers to a situation where the number of fuzzy rules increases exponentially with the number of input variables. Therefore, six features were used in the diagnosis system. These features have to be very accurate, so the features selection algorithm, Greedy feature flip (G-flip) algorithm was used to determine our best 6 features out of the dataset of features that were extracted previously.

4.1 ANFIS Structure

In this paper, for the classification method the ANFIS algorithm was used in order to classify the trial images into images that belong to one of the three different types of skin lesions mentioned earlier.

So ANFIS’s network organizes two parts like fuzzy systems. The first part is the antecedent part and the second part is the conclusion part, that are connected to each other by rules, in network form. If ANFIS in network structure is shown, that is demonstrated in five layers (Alturki, 1999) Where the first layer executes a fuzzification process, the second layer executes the fuzzy AND of the antecedent part of the fuzzy rules, the third layer normalizes the membership functions (MFs), the fourth layer executes the consequent part of the fuzzy rules, and finally the last layer computes the output of fuzzy system by summing up the outputs of fourth layer. Here for ANFIS structure (Figure 2) two inputs and two labels for each input are considered. The feed forward equations of ANFIS are as follows: (Kim,1993; Alturki, 1999 and Ghomsheh, 2007)

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \ i = 1, 2$$

(3)
\[
\bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2
\]  

(4)

\[
f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = \bar{w}_1 f_1 + \bar{w}_2 f_2
\]  

(5)

Where \( f_1 = p_1 x + q_1 y + r_1 z \) and \( f_2 = p_2 x + q_2 y + r_2 z \)

In order to model complex nonlinear systems, the ANFIS model carries out input space partitioning that splits the input space into many local regions from which simple local models (linear functions or even adjustable coefficients) are employed. The ANFIS uses fuzzy MFs for splitting each input dimension. The input space is covered by overlapping MFs, which means that several local regions can be activated simultaneously by a single input. As simple local models are adopted in ANFIS model, the ANFIS approximation ability will depend on the resolution of the input space partitioning, which is determined by the number of MFs in ANFIS and the number of layers. Usually MFs are used as bell-shaped with maximum equal to 1 and minimum equal to 0 such as (Alturki et al., 1999; Ghomsheh et al., 2007 and Odeh et al. 2009):

\[
\mu_A(x) = \frac{1}{1 + \left[\frac{(x - c_i)}{a_i}\right]^{2b_i}}
\]  

(6)

\[
\mu_A(x) = \exp\left\{-\left[\frac{(x - c_i)}{a_i}\right]^{2b_i}\right\}
\]  

(7)

Where \( \{a_i, b_i, c_i\} \) are the parameters of MFs which are affected in shape of MFs.

![Figure 2](image.png)

*Figure 2  The equivalent ANFIS (type-3 ANFIS)*

The ANFIS uses member function for each input. The training was run for 10 iterations. The network performance was evaluated on the checking set, after each iteration, by calculating the root-mean-square errors (RMSE)

\[
RMSE = \sqrt{\frac{\sum_{k=1}^{K}(y_k - \hat{y}_k)^2}{K}}
\]  

(8)

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k is the pattern number, where $k=1,2,…,K$, $Y_i$ is the correct value, and $\hat{Y}$ is the output value from the ANFIS. The RMSE was also evaluated on training data set in every iteration. The optimal number of iterations obtained were 9 epochs by the time RMSE reached its minimum value. We then convert the error from RMSE to percentage error.

5 EXPERIMENTAL RESULT

Before applying this methodology of the classification, the posed diagnosis problem is divided into two tasks:

- Easy Task: the distinction between cancerous or pre-cancerous images and psoriasis cases. This means, two classes: class 1 (cancer and pre-cancer) consists of 33 images of Actinic Keratosis and 34 images of Basal Cell Carcinoma, and class 2 (psoriasis) consists of 67 images.

- Difficult Task: the detection of the cancer (Basal Cell Carcinoma) within the database is composed from 50 images of Actinic Keratosis cases and 50 images of Basal Cell Carcinoma. This means, two classes: class 1 (cancer) and class 2 (pre-cancer).

The training data set was made up from 80% of the overall data and the other 20% of the data is considered as testing data set.

Three versions of these data sets are used where each version was randomly disordered in order to cross-validate the results.

After applying the methodology and running the classification algorithm for 10 iterations, it reached the minimum RMSE value at the ninth epoch. The classification accuracy in both of the easy task and the difficult task, for each of these three versions are shown below, in Table 1. The ANFIS structure information is shown in Table 2.

<table>
<thead>
<tr>
<th>Version</th>
<th>Easy task</th>
<th>Difficult task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Version 1</td>
<td>99.77</td>
<td>94.18</td>
</tr>
<tr>
<td>Version 2</td>
<td>99.39</td>
<td>90.83</td>
</tr>
<tr>
<td>Version 3</td>
<td>99.49</td>
<td>92.03</td>
</tr>
<tr>
<td>The average accuracy</td>
<td>$99.55 \pm 0.2$</td>
<td>$92.35 \pm 1.7$</td>
</tr>
</tbody>
</table>

*Table 1. The classification accuracy of the easy and difficult task*

<table>
<thead>
<tr>
<th></th>
<th>Easy task</th>
<th>Difficult task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes:</td>
<td>1503</td>
<td></td>
</tr>
<tr>
<td>Number of linear parameters:</td>
<td>5103</td>
<td></td>
</tr>
<tr>
<td>Number of nonlinear parameters:</td>
<td>54</td>
<td></td>
</tr>
<tr>
<td>Total number of parameters:</td>
<td>5157</td>
<td></td>
</tr>
<tr>
<td>Number of training data pairs:</td>
<td>80</td>
<td></td>
</tr>
<tr>
<td>Number of checking data pairs:</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>Number of fuzzy rules:</td>
<td>729</td>
<td></td>
</tr>
</tbody>
</table>

*Table 2. The ANFIS structure information.*

From results tabled above, it can be seen that the using of ANFIS classification algorithms as a diagnosis system for biomedical problems, have a high level of efficiency performance, where it can accurately predict the testing in the easy task by approximately 100%, and in the difficult task by 92%, which means that the ANFIS is powerful enough to be used as a diagnosis system. This work was
implemented by using MATLAB 7.5 under Windows Vista with intel Centrino processor running at 1.87 Ghz. The time spent to get the result of this classification was about 120 minutes.

The ANFIS classification algorithms KNN classifier optimized with GA represents a valid tool to study the significance of different features for a given diagnosis problem (Ros et al., 2003, Odeh et al., 2006). We have tested other classifiers such as KNN classifier optimized with GA, and artificial neural networks (ANN) (Multilayer Perceptron) yielding lower level of accuracies and requiring much longer computing times. The low performance level of the ANN classifiers is mainly due to the limited number of samples (167 images) of the database.

6 CONCLUSION

This paper introduces the adaptive neuro-fuzzy inference system (ANFIS) as a diagnosis system for biomedical problems; the diagnosis of skin lesions. This system showed good performance accuracy, especially when compared with other systems that use the same database of fluorescence images. It can be concluded that the diagnosis systems based on ANFIS, can also be applied to other biomedical field applications, like breast cancer, EEG signals, ECG signals .. etc. Consequently, this paper validates the optimization technique of the different features to a high level of classification accuracy, where these features were extracted by image processing and then selected by using G-flip algorithm. Other published classification methods, such as K-nearest neighbour (Ros et al., 2003, Mies et al. 2001, and Odeh et al., 2006) with genetic algorithms (Odeh et al., 2008) which uses the same data set as our study, have a lower level of accuracy results.

The result of this classification method showed that by using ANFIS, produces better result than with other algorithms for diagnosis systems, in the field of biomedical studies.

References


