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Adaptive Neuro-Fuzzy Inference System For Medical Image Classification –A Review

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2022 4th International Conference on Cybernetics and Intelligent System (ICORIS) | 978-1-6654-5395-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICORIS56080.2022.10031548

***Abstract*— Medical image has now been widely used as the object in research particularly in artificial intelligent. Classification automation on medical image can assist to provide information or as the second opinion for the paramedics in doing a medical action and giving a diagnosis for the patients. One of the algorithms as the classifier is the adaptive neuro-fuzzy inference system (ANFIS) method – a hybrid method combining the fuzzy logic and neural network. ANFIS algorithm is the fuzzy inference system (FIS) implemented into the adaptive fuzzy neural network framework. This method combines the explicit knowledge as the representation from FIS and learning ability from the artificial neural network. This paper presents the discussion and the review of the adaptive neuro-fuzzy inference system (ANFIS) algorithm as the classifier in medical image classification. A number of research that have been conducted on the medical image object are evaluated and discussed in terms of their strengths and weaknesses.**

Keywords — ANFIS, Medical Image Classifiaction, Neuro-fuzzy.

I. Introduction

Disease diagnosis on human in today development has been mostly assisted by means of a system that is able to provide the useful information for the paramedics. The research on the automated diagnosis system have been widely conducted using the medical image data. The medical image can be taken by the paramedics by means of devices such as CT-Scan, USG, or MRI. The main idea or the main purpose of most of the systems proposed is to cope with the human error and more effective diagnosis time and to give information that can help the doctors in taking a medical action. One of the methods used is the adaptive neuro-fuzzy inference system (ANFIS), a set of rules and an inference method combined in a connected structure to later be used to do training and adaptation [1]. Two of models as the adaptive networks that can function as in the fuzzy inference system are ANFIS and Dynamic Evolving Neuro Fuzzy Inference System (DENFIS) [2]. Most of papers on neuro-fuzzy use the backpropagation learning algorithm to generate the fuzzy rules with the function of membership using the Gauss model given separately. This then causes the greater number of parameters to be generated if the number of input variables are added. Mizumoto in research [3] introduced the learning algorithm on neuro-fuzzy without a must to change the form of fuzzy rules. This method is very efficient particularly if used to identify the non-linear functions. ANFIS is an architecture that functionally is similar with the fuzzy rule based on the Sugeno model. The architecture of ANFIS is also similar with the neural network with the radial function with a few of certain limitations. It can be stated that ANFIS is a method in which in doing the rule, the learning algorithm is used to a set of data. In ANFIS, it is also possible to make each rule to be able to adapt. Sulzberger in research [4] developed a method to optimize the fuzzy rules using the artificial neural networks and the development of a new model that enables the translation of the fuzzy rules and function of the membership in the form of network. Osowski [5] developed the neuro-fuzzy through the self-organization learning to the data trained to obtain the optimal number of fuzzy rules and to generate the central of membership function. This paper discusses about a number of researches that used the ANFIS method in classifying the diseases such as cancer [6] [7] [8], tumor [9], diabetes diseases [10], dan optic nerve diseases [11] [12]. In many applications, ANFIS model is used as a classifier in which the input vector of ANFIS model consists of several features extracted from the results of image segmentation. Some discussions about the strengths of ANFIS method and the comparison of the result with other method are presented in this paper.

The rest of this paper is structured as followed. In Section II, we introduce the overview structure and learning algorithm of ANFIS. Section III describes the contibution of ANFIS as a classifier and Section IV describe the conclusion.

II. ANFIS

ANFIS (Adaptive Neruo Fuzzy Inference System) is an architecture that is functionally similar with the fuzzy rule based model of Sugeno. The ANFIS architecture is also similar with the artificial neural network with the radial function with few certain limits. It can be stated that ANFIS is a method in which in doing rule arrangement, it uses the learning algorithm towards

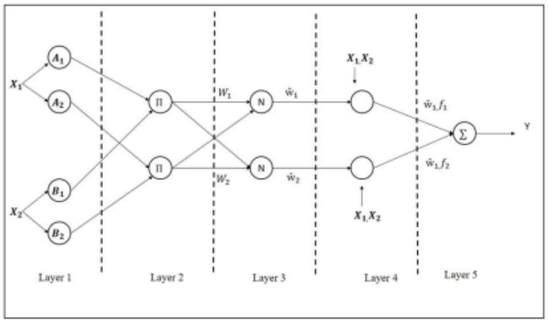

Fig. 1. ANFIS Architecture

a set of data. In ANFIS, it is also possible for the rules to adapt. As stated in book [13] to make the network with the radial base function equivalent with the rule based fuzzy of Sugeno model Order 1, the following limitations are needed:

- The rules must have the similar aggregation method (weighted average or the weighted addition) to produce all outputs.
- The number of activation functions must be equal with the number of fuzzy rules (IF-THEN)
- If there are some inputs in their rule bases, then each activation function must be equal with the membership function of each input.
- The activation function and fuzzy rules must have a similar function for the neurons and the rules existing in the side of its output.

A. *Structure of ANFIS*

For ease, it is assumed that there were 2 inputs of $x_1 x_2$ and one output y. There are two rules in the basis of Sugeno model [14] :

$$if\ x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1 \text{ Then } y_1 = C_{11}X_1 + C_{12}X_2 + C_{10}$$
$$if\ x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_2 \text{ Then } y_2 = C_{21}X_1 + C_{22}X_2 + C_{20}$$

If α predicate for the rules to those two rules is w_1 and w_2, then the weighted average can be calculated as follows:

$$y = \frac{w_1 y_1 + w_2 y_2}{w_1 + w_2} = \hat{w}_1 y_1 + \hat{w}_2 y_2 \qquad (1)$$

The ANFIS network as shown in Figure 1 consists of the following layers [15] :

1. Each neuron x_i in the first layer is adaptive to the parameter of an activation function. The output of each neuron can be in the form of the membership level given by the membership function of input.
The output of each neuron is the degree of membership given by the input membership function,

$$\alpha_{A1}(x1), \alpha_{B1}(x2), \alpha_{A2}(x1), atau\ \alpha_{B2}(x2).$$

For example, the membership function is given as:

$$\mu(x) = \frac{1}{1+|\frac{x-c}{a}|^{2b}} \qquad (2)$$

Where {a,b,c} refer to the parameters, commonly as b=1. If the values of the parameter changes, then the form of the curve occurred would also change. The parameters in that layer commonly is known as the premise parameters.

2. Each neuron in the second layer is in the form of fixed node whose output is the result of the input. The operator commonly used is AND. Each node represents α predicate from the rulex_i.
3. Each neuron in the third layer is in the form of fixed node as the result of the ratio calculation of the α predicate (w) from the rule i to the number of all α predicates.
4. Each neuron in the fourth layer is the adaptive node towards an output with $\hat{w}_i$ as the normalised firing strength in the third layer and $\{C_{i1}, C_{i2}\ C_{i0}\}$ are the parameters in the neuron. The parameters in the layer is called as the consequent parameters.

$$\hat{w}_i = \frac{W_i}{W_1 + W_2}\text{, with } i\text{=1,2.} \qquad (3)$$

5. Each neuron in the fifth layer is the fixed node as the sum of all inputs

$$\hat{w}y_1 = \hat{w}_i(C_{i1}X_1 + C_{i2}X_2 + C_{i0}) \text{ With } i\text{=1,2..} \quad (4)$$

with $\hat{w}_i$ is a normalised firing strength in third layer and $\{C_{i1}, C_{i2}\ C_{i0}\}$ is parameters in neuron. This parameters in each layer is a consequent parameters.

6. Each neuron in the fifth layer is a fixed node which is the sum of all inputs.

B. *Learning Algorithm of ANFIS*

In further step, the training of adaptive network was conducted to obtain the values of parameter a and c in equation (2). By taking the value of b=1, then the equation (2) becomes:

$$\mu(x) = \frac{1}{1+|\frac{x-c}{a}|} \qquad (5)$$

To improve a and c, error propagation model was used using the concept of gradient descent. For instance, an adaptive network has 5 layers as many as N(L) neuron in the layer L, then the number of error quadrat (SSE) in the layer L data to -P, $1 \le p \le N$ is:

$$E_p = \sum_{k=1}^{N(L)} (d_k - X_{L,k})^2 \qquad (6)$$

If the form of the adaptive network is as shown in Figure 1, which it only has one neuron in the output layer, then the error propagation to the layer 5 can be formulated into:

$$\varepsilon_{out} = \frac{\partial Ep}{\partial x_{out}} = -2\,(d_{out} - x_{out}) = -2\left(y_p - y_p^*\right) \qquad (7)$$

where y_p refers to the target of training data output to -p, and y_p^* refers to the network output to the training data to -p. In the fourth layer, the error propagation has two neurons formulated into as shown as follows in which n5 refers to the neuron in the fifth layer.

$$\varepsilon_n = \left(\frac{\partial Ep}{\partial x_{out}}\right)\left(\frac{\partial f_{13}}{\partial x_{n5}}\right) = \varepsilon_{13}\left(\frac{\partial f_{13}}{\partial x_{n5}}\right) = \varepsilon_{out}(1) = \varepsilon_{out} \qquad (8)$$

since $f_{out} = \hat{w}_1 f_1 + \hat{w}_2 f_2$, maka $\frac{\partial f_{out}}{\partial(\hat{w}_1 f_1)} = 1$

Furthermore, the error propagation to the 3rd layer has two neurons and it can be formulated as follows in which n3 refers to the neuron that lies in the 3rd layer and n4 is the 3rd and 4th layer.

$$\varepsilon_{n3} = \left(\frac{\partial Ep}{\partial x_{out}}\right)\left(\frac{\partial f_{13}}{\partial x_{n4}}\right)\left(\frac{\partial f_{n4}}{\partial x_{n3}}\right) = \varepsilon_{n4}\left(\frac{\partial f_{n4}}{\partial x_{n3}}\right) = \varepsilon_{n4} f_1 \qquad (9)$$

since $f_{n4} = \hat{w}_1 f_1$, maka $\frac{\partial f_{n4}}{\partial(\hat{w}_1)} = f_1$

Furthermore, the error propagation to the 2nd layer has two neurons (i.e. n31 and n32) and it can be formulated as follows:

$$\varepsilon_{n2} = \varepsilon_{n31}\left(\frac{w_2}{(w_1+w_2)^2}\right) + \varepsilon_{n32}\left(\frac{w_2}{(w_1+w_2)^2}\right) \qquad (10)$$

if $\varepsilon_{n31} = \frac{w_1}{w_1+w_2}$ then $\frac{\partial f_{n31}}{\partial(\hat{w}_1)} = \left(\frac{w_2}{(w_1+w_2)^2}\right)$

and $\varepsilon_{n32} = \frac{w_1}{w_1+w_2}$ then $\frac{\partial f_{n32}}{\partial(\hat{w}_1)} = -\left(\frac{w_2}{(w_1+w_2)^2}\right)$

The last one is to the 1st layer in which there are 4 neurons, then the propagation error is presented as follows:

$$\varepsilon_{n11} = \varepsilon_{n21}\left(\frac{\partial f_{n21}}{\partial x_{n11}}\right) = \varepsilon_{n21}\mu_{B1}\,(x_2) \qquad (11)$$

$$\varepsilon_{n12} = \varepsilon_{n22}\left(\frac{\partial f_{n22}}{\partial x_{n12}}\right) = \varepsilon_{n21}\mu_{B2}\,(x_2) \qquad (12)$$

$$\varepsilon_{n13} = \varepsilon_{n23}\left(\frac{\partial f_{n23}}{\partial x_{n13}}\right) = \varepsilon_{n23}\mu_{A1}\,(x_1) \qquad (13)$$

$$\varepsilon_{n14} = \varepsilon_{n24}\left(\frac{\partial f_{n2}}{\partial x_{n1}}\right) = \varepsilon_{n2}\mu_{A2}\,(x_1) \qquad (14)$$

Furthermore, the error value can be used to seek the error information towards the parameter a(a_{11} and a_{12} to A_1 and A_2; a_{21} and a_{22} to B_1 and B_2 and c (c_{11} and c_{12} for A_1 and A_2 and c_{21} and c_{22} for B_1 and B_2. From here, the value of the changes in the parameter a_{ij} and c_{ij} (Δa_{ij} and Δc_{ij}) can be determined as follows:

$$\Delta a_{ij} = \eta \varepsilon_{aij}\, x_i \text{ and } \Delta c_{ij} = \eta \varepsilon_{cij}\, x_i \qquad (15)$$

where η refers to the learning rate that lies in the interval [0,1]. Thus, the new value of a_{ij} and c_{ij} is a_{ij}= a_{ij} (old) + Δa_{ij} and c_{ij} = c_{ij} (old) + Δc_{ij} (16)

III. ANFIS AS A CLASSIFIER

Neuro-fuzzy systems are the fuzzy systems using the ANNs theory to determine their properties (fuzzy sets and fuzzy rules) by processing the data samples [16]. A specific approach in neuro-fuzzy development is the adaptive neurofuzzy inference system (ANFIS), which has shown some significant results as a classifier in medical image. This section describes the implementation of ANFIS as a classifier in several medical images. However, according to [17] some advantages of ANFIS include

- Refining fuzzy if–then rules to describe the behavior of a complex system
- Not requiring prior human expertise that is often needed in fuzzy systems, and it may not always be available
- Presenting greater choice of membership function to use
- Bringing very fast convergence time

And according to the [18], ANFIS classifier drawbacks :

- Low accuracy if input vector is large
- Poor classification result if input sample are not enough while there are many nodes in ANFIS.

A. Brain Tumor

A research conducted by [19] proposed a system to detect the brain cancer based upon the shaped-based feature extraction to differentiate the benign and malignant. The input variabel used was the shape distance (SD) and shape similarity measure (SSM) in fuzzy tools and it used the fuzzy rule to evaluate the output. The classifier used was neural network system (NNS), named Levenberg-Marquardt (LM) in which the fed-forward back propagation learning algoritm was used for the pross training of the NN to obtain the status of the brain cancer.

For the classifier, it used neuro-fuzzy tools. The experiment showed a good performance with the feature of SD and SSM obtained from ROI brain tumor lesions. This shape-based feature became a variable input and using the fuzzy rules, this research was able to detect the status of the brain cancer. The method proposed was trained with MR image dataset from 16 cases in which these cases were put into ANN with the structure of 2 input neurons, one hidden layer consisting of 10 neurons, and 2 ouput neurons. From the 16 sample of database, 10 dataset were used as training, 3 dataset were used as the validation and 3 dataset were used as the testing used in the ANN classification. From SSM confusion matrix, it obtained the number of ouput dataset of true positive, false positive dan false negative, namely 6,0, 10 and 0 respectively. Sensitivity, specificity and accuracy of each reached 100%.

Research in [20] provided a proposal to detect the brain tumor using three features: Minimum Gray Level Pixel value occured (MinGL), Maximum Gray level pixel occured (MaxGL) and

TABLE I. COMPARISION RESULT ON [14]

Algorithms	Sensitivity (%)	Specificity (%)	Accuracy (%)
DWT + SOM	95.13	92.02	92.72
DWT + PCA + KNN	96.02	95.03	97.02
Second oreder + ANN	91.42	90.01	92.22
Texture combined + ANN	95.04	96.01	97.22
Texture combined + SVM	97.08	96.06	97.09
FCM	96	93.03	86.06
K-Mean	80	93.12	83.03
Proposed Method (ANFIS)	96.06	95.03	98.67

Mean of Gray level value occured (MeanGL) in the objects of membrane, ventricle, dark abnormality, and light abnormality. Proposed method used three layers of neural network with 500 nodes in the first input layer, 1-50 nodes in the hidden layer, and 1 node in the ouput layer. In the input to the hidden layer, it used the tanh and sigmoid activation function, while in the hidden layer to the output layer it used the log sigmoid function. ANFIS was used as a classifier in which the result showed a better result compared to Fuzzy classifier and BPN as shown in Table 2.

TABLE II. CLASSIFIER COMPARISION BASED ON RESULT [20]

Average Convergence time period (sec)	Average Mean Squared Eror	Average Classification Accuracy %	Classifier
1540	0,1048	93.03	ANFIS
15380	00.25	88.06	Fuzzy
16,245	00.37	85.65	BPN

The combination of neural network and fuzzy logic was also proposed in the research [21]. The object used was the MRI image of Brain tumor using the feature texture adapted using the GLCM method. The classifier used was ANFIS with 2 membership functions and 64 rules frame. The structure of ANFIS used consisted of 6 inputs and a single output. The 6 inputs represented each difference in the feature texture obtained from each image. Each input was given two generalized beell curve membership function and the output was represented with two linear membership functions.

The total 161 nodes were used in this architecture. The result of the proposed method was then compared to other two classifiers: BPN and fuzzy classifier. With the result showing that ANFIS was able to obtain the accuracy of 93.3%, then, this value was higher than that of BPN and fuzzy classifier. Research [22] used the ANFIS model as a classifier to detect the brain tumor. The feature of Gray Level Co-occurance Matrix (GLCM) was used to differentiate the abnormal and normal brain tumor. The result of the proposed method was then compared to the result of Fuzzy C Means (FCM) and K Nearest Neighbors (KNN) method. The result showed that the performance of ANFIS as the classifier was better by achieving the values of accuracy of 98.67%, sensitivity of 96,6%, and specificity of 95,3%. These results were higher than that of the methods of FCM and KNN as shown in Table 2.

A research [23] used the feature of GLCM and dual tree complex wavelet transform multi-scale decomposition differentiating the stages from the brain tumor into benign, malignant, and normal. ANFIS was used as a classifier. Different from the research in [24] using the Principal Component Analysis (PCA) method to extract the feature in differentiating the MR image in the normal and abnormal brain. The classifier used ANFIS with seven neurons connected to seven features. The output layer consisted of one neuron differentiating whether it was included as normal and abnormal. A research [25] used ANFIS as a classifier to detect the existence of tumor of Glioblastoma Multiforme (GBM). The architecture used in the research can be seen in Figure 2 as follows.

Furthermore, research in [26] used the neural network, fuzzy cluster method to identify the abnormal brain tumor region on the MRI image. The spatial fuzzy clustering method was applied to detect the brain tumor part in the MRI scanning images. In the classification stage, BPFNN has been implemented to find the brain tumors in images. This proposed Back Propagation Fuzzy Neural Network classifier technique has been used to classify the benign and malignant brain tumor images. The result showed that BPFNN classifier could provide a fast and accurate classification compared to other neural network methods and it could be effectively used for classifying the brain tumor with the high level of accuracy. A research in [27] used the Non-Sub Sampled Countourlet Transform (NSCT) to enhance the brain image and it used the texture feature later to be trained using the ANFIS classifier. The object used was the brain image that identified the disease of Glioma brain MRI image. Table 3 shows the summary of the results and some parameters used in the research using ANFIS as the classifier to detect and classify the disease in the brain.

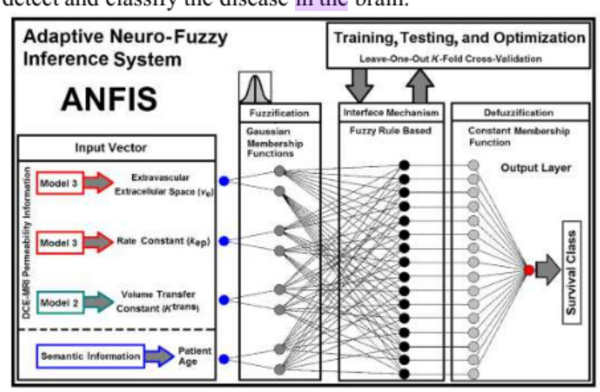

Fig. 2. Adaptive Neuro-fuzzy Inference System (ANFIS) structure and flow information for glioblastoma multiforme (GBM) [25].

B. Breast cancer

A number of artificial intelligent techniques have been applied in radiology to make a prediction and assessment to the biopsy in the breast cancer. Some of techniques that have been developed include the ones using Artificial Neural Network, Convolutional Neural Network, Radial Basis Network, General Regression Neural Network, and Hybrid technique between fuzzy logic and Neural network known as Neuro-Fuzzy [28]
One of the develop of Neuro-Fuzzy concept is known as the Adaptive Neuro-Fuzzy Inference System (ANFIS), where it is able to connect functions existing in a set limited to any levels. In journal written by Huang et al. (2010), classification in the dataset of breast cancer taken from the UCI machine Learning Repository Mammographic Mass consisting of BI-RADS assessment, patients age, and BI-RADS attributes with ground truth from 516 benign and 445 malignant mass was conducted [29]. ANFIS was used to build a model of classification prediction between malignant and benign with an architecture consisting of 5 layers in which layer 1 functioned to generate the membership grades for each set of input data vectors, layer 2 implemented the fuzzy AND operator, while layer 3 acted to scale the firing strengths. The output of layer 4 was comprised of a linear combination of the inputs, multiplied by the normalized firing strength w: $Y = w(pX + r)\ y$ where p and r were the adaptable parameters, and layer 5 was a simple summation of the output of layer 4. The training process consisted of two-pass process by using the number of each epoch, output resulted from layer 4 and 5 calculated using the least-square regression method, and the output of the ANFIS was calculated and the errors propagated back through the layers to determine the premise parameter (Layer 1) updates, This research showed the result with the performance of the ROC value of 92.80%, compared to the other classifier methods such as PSO based ANN with only by 91.10%.

ANFIS model with hybrid learning algorithm was also used by Fatima et al. (2012) to classify the breast cancer with the dataset taken from University of California Irvine (UCI) Machine Learning Repository consisting of 699 data with 65.5% classified as benign and 34.5% as malignant. Here, the hybrid learning algorithm was used to identify the existing parameters in ANFIS in which the learning algorithm referred consisted of 2 phases: in the forwarding process to the hybrid learning algorithm, node outputs values going forward until layer 4 and the consequent parameters were identified by the least square method, and when the backward passes, the premise parameters

were adjusted using the gradient descent method. The result of the research showed that the hybrid method as the combination of back propagation and least square has given a better result with the accuracy of 98.25% in comparison to the

TABLE III. SUMMARY RESULT ON ANFIS CLASSIFIER ON BRAIN DISEASE

Result	Dataset	Stucture & Parameter	Feature	Algorithm
Sensitivity, specificity and accuracy and accuracy: 100% , TP,FP,TN,FN : 6,0,10,0	MR Image	Three layer NN (one input,one hidden layer,one output) feed forward with 2 input sigmoid hidden neurons and linier output neurons. 10 number of hidden neuron	Shape distance (SM), Shape Similarity measure (SSM)	Levenberg-Marquardt (LM), ANFIS classifier, and ANN Classification
Classification Accuracy:93.3% mean squared error : 0.151	MR Image	tiga layer neural network 500 nodes on first input layer, 1-50 nodes on hidden layer, dan 1 node on output layer. tanh sigmoid activation function and log sigmoid function	MinGL,MaxGL, MeanGL. (membrane,ventricle,dark abnormality,dan light abnormality	ANFIS
Accuracy Classificartion : 93.3% convergence time period : 1549 sec	MR Image	membership function adalah 2 dan menggunakan 64 rules frame Struktur dari ANFIS yang digunakan terdiri dari 6 inputs dan single output and total ndes 161 iteration number 200. Step for parameter adpation 0.01 dan error tolerance 0.001.	Texture Feature (GLCM)	ANFIS
Accuracy Classification : 98.67%	MR Image	7 inputs and single output with 16 fuzzy rules Input with bell curve membership function and output linear membership function	Texture Feature (GLCM)	ANFIS
The CCF :84.8%. High diagonal elements of the confusion matrix (81.8%, 90.1% and 81.8% for Class 1, Class 2 and Class 3, respectively)	DCE-MRI	K-fold cross-validation (K = 33) technique was employed for training, testing and optimization of ANFIS	PK Parameters	ANFIS And Nested Model Selection
Acc : 90%,Sensitivity : 100%,Specificity : 75%	MRI Images	nodes in the input layer is 9 representing features extracted from the ROI. The number of nodes in the hidden layer is was decided experimentally, The network is trained using log-sigmoid activation function with a learning rate of 0.1	Texture Feature (GLCM)	Back propagation Fuzzy Neural Network
- Acc : 98.5 %	MRI Images	single input and output layer with five intermediate hidden layers, each hidden layer have 10 neuron	Texture Feature (GLCM), Law's texture	ANFIS

one only using the back propagation that only obtained the accuracy of 64.91%. The further research was conducted by Ashraf et al. (2010) using a proposed approach that is Information Gain ANFIS or known as IGANFIS [30]. The Information Gain aims to select the attributes or features with the highest values in which there were total 9 attributes or features taken from Wisconsin Breast Cancer Diagnosis (WBCD) with 699 record data. The output of information gain was the input feature that would be used in ANFIS as the

training and testing data. The result obtained from the proposed approach showed the accuracy of 98.24%. This research also conducted a comparison of the testing towards a number of methods that is ANFIS proposed by Atashi et al. (2017) [31] with the accuracy of 59.90% and SANFIS with (IG-SCANFIS) [33]. Information gain method was applied to reduce the dimension of the attribute of feature and to apply the feature attribute previously selected as the input attribute in SCANFIS. In other words, the Information Gain was used as the method in selecting the features to be used as the input. The method and SCANFIS controller used the Sugeno fuzzy rules and the weighted sum method to calculate the total output, and eliminate the need for a large amount of computational work to clarify the conventional fuzzy system center of gravity method. Thus, the data processing was minimized, and according to the neural network Self-learning characteristics, it could improve the performance of fuzzy systems. The accuracy obtained from the proposed method was 99.44%. The summary of the result on ANFIS classifier on Breast disease is presented in Table 4.

TABLE IV. SUMMARY RESULT ON ANFIS CLASSIFIER ON BREAST CANCER

Author	Algorithm	Result	Dataset
		Accuracy	
Fatima et al (2012)	Last square and backpropogation	98.25.00	University of California Irvine (UCI) 699 dataset
Huang et al (2012)	Last-square regresion and backpropoagation	92.08.00	University Erlangen- Nuremberg (961 dataset)
Ashraf et al (2010)	Information Gain ANFIS	98.24%	Wisconsin Breast Cancer Diagnosis (699 dataset)
Elloumi et all (2016)	ANFIS and PSO optimation algorithm (SCNF)	99.12%	Wisconsin Breast Cancer Diagnosis (699 dataset)
Atashi et all (2017)	ANFIS	94.44%	Wisconsin Breast Cancer Diagnosis (699 dataset)
Liang et all (2017)	Information Gain Subtractive ANFIS (IG-SANFIS)	99.44%	Wisconsin Breast Cancer Diagnosis (699 dataset)

accuracy of 96.07%. The development of the hybrid method in neuro-Fuzzy has always been being conducted. In 2016 Elloumi et al. conducted an approach named Self-Constructing Neuro Fuzzy (SCNF-PSO) [32]. This algorithm used the self-constructing method to determine the number of rule *J* and to connect the antecedent and consequence parameter by considering 9 input parameters as the reference in the method proposed. Thus, in SCNF classifier, it could generate the output

that can do the classification of benign (with the value 0) or tumor (with the value of 1), and PSO algorithm implemented to seek the most optimal value from the antecedent and consequence parameter Maximizing the object of the function. PSO algorithm executed to reach the maximum value from the objective function or the maximum number of iterations. This phase obtained the optimal parameter value in SCNF classifier, To obtain the best performance of the classification process, then an objective function for the particle *m*: $H\ (P^{(m)} = \alpha.ACC + \beta.Se + \gamma.Sp$ was defined in which $\alpha,\beta\ and\ \gamma$ were represented from the weight of overall accuracy from the classification process (ACC). *Se* refers to sensitivity and *Sp* refers to the specification and $P^{(m)}$ is the particle of position vector by the concatenation of the antecedent and consequence Parameters of all obtained rule. Using the dataset from Wisconsin Breast Cancer Diagnosis (WBCD) through the method approach proposed, it obtained the accuracy level of 99.12%. The method development in diagnosing the breast cancer furthermore was proposed by Liang et al. (2017) using the hybrid method namely Information Gain method and the subtractive clustering adaptive neural fuzzy inference system

C. *Retinal vessel*

As a classification method, ANFIS was also applied on retinal image with one of purposes is to analyze the object on the retinal image to analyze the form of the blood vessel on the retina. The result of the analysis could be used as an initial step to diagnose and detect the Diabetic Retinopathy for the patients of diabetic disease. Several research related to detecting blood vessels in the retina have been conducted using various methods, especially in the classifier method such as Bayesian classifier by approaching the level set to detect the thick vessels in the retinal image where the accuracy obtained by this method reached 95.29% [34], and with SVM classifier achieving the accuracy of 95.1% [35]. Based on the results obtained from the accuracy of the classifier method, Prakash et al, (2017) proposed a model approach with multilayer classifier ANFIS to obtain the better accuracy. The proposed approach model showed 98.45% accuracy based on the public datasets of DRIVE and STAR[36]. The high accuracy achieved in the classification process cannot be apart from how to do the data pre-processing in the data where each pixel in the retina fundus image was expressed with 8D-feature vectors v = {f1, f2, f3, f4, f5, f6, f7, f8. The extracting gray level features included f1, f2, f3, f4 and f5, F6 representing the extracted orientation feature, f7 represented the extract morphological feature, and f8 represented the Gabor feature extract.

This factor is an input in the classifier. Classification process produced 2 classes: vessel pixel or non-vessel pixel. To improve the accuracy of the classifier, the design of ANFIS used multilayer, which consisted of input layers, multiple hidden layers with a single output layer. A multi-scale scale transformed the images from the retina into a number of features where a number of extracted features was similar with the number of neurons in the input layer.The results of the accuracy was improved using the hidden layers, each of which was built by setting 15 neurons after several iterations. Single neurons at the output layer classified each pixel in the retina image. Borah (2015) utilized ANFIS as a classifier method for retina recognition. The structure of ANFIS used consisted of 5 layers where the first layer performed fuzzification, and the second layer generated the response of the network due to fuzzy inputs. The third layer performed normalization. For the fuzzy responses, adaptive update was done by the fourth layer. The last layer performed the task of summation of all the outputs[37]. The fuzzification on the first layer used Generalized Bell MFs and Gaussian MFs. Gaussian functions are well known in the fields of probability and statistics; they possess some useful properties such as invariance under multiplication and Fourier transform. The bell MF has more parameters compared to the Gaussian MF, so it can approach a non-fuzzy set if b→∞[38]. For the ANFIS training method, it uses Least-square with the back propagation gradient descent with the average of training using 10-200 epoch and total 10 membership functions. The ANFIS model proposed was able to reduce the epoch by 50%, and the training time required was in the range of 1.9- 2.1 for each sample compared to ANN method and the accuracy obtained with ANFIS classifier was 95%, This paper provides a suggestion for further research on how to make an improvement in the architecture of ANFIS to increase the accuracy. The comparison of the accuracy of some methods that have been presented with the subject of retinal blood vessel showed the performance of the ANFIS classifier with the highest accuracy as shown in Table 5.

TABLE V. COMPARASION RESULT IN DIFFRENT CLASSIFIER FOR RETINAL VESSEL

Author	Algorithm	Result Accuracy	Dataset
Xiao, 2013	Bayesian classifier	95.29%	DRIVE and STAR
Siva, 2014	SVM classifier	95.10%	DRIVE and STAR
Borah, 2015	ANFIS classifier	95%	DRIVE and STAR
Prakash, 2017	ANFIS with multiple layer	98.54%	DRIVE and STAR

D. *Servic cancer*

The paper written by Al-batah (2014) related to the cervical cancer into 3 classes: normal, low-grade squamous intraepithelial lesion (LSIL) and high-grade squamous intraepithelial lesion (HSIL) based on the recognition using Multiple Adaptive Neuro-Fuzzy (MANFIS) [39] in which the architecture of MANFIS had 6 input of *X1,X2,X3,X4,X5,and X6,* and 3 output of *f1, f2 and f3*, as shown in Figure 3. A hybrid learning algorithm which combines least squares estimation and back propagation is used for membership function parameter estimation. The advantage of hybrid method is that it uses back propagation for parameter associated with input membership function and least square estimation for parameters associated with output membership. Total 500 single cell images were used in the classification process (376 normal, 79 LSIL and 45 HSIL) in which 80% of total images (400 images) were used for the data training and 20% (100 image cells) were used as the data testing.

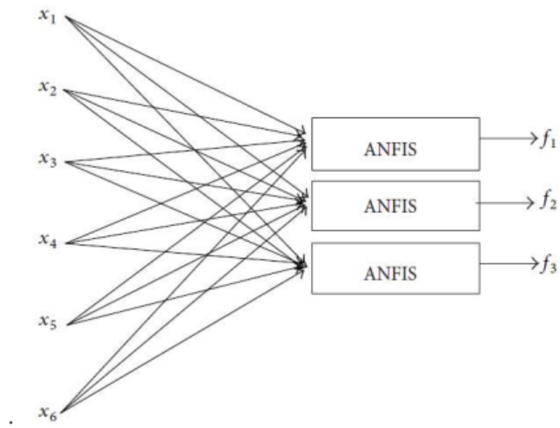

Fig. 3. The architecture of the MANFIS

The accuracy percentage of each class was calculated by dividing the summation of the predicted number of cells over the summation of the original number of samples in each of all folds (k-fold = 5) and produced the results for overall classification process of 96.3% and 94.2% for training and testing phases.

E. *Thyroid*

Thyroid is an important gland located in the lower neck producing hormones and affects every cell in tissue, and regulates the metabolism in the body. The excessive hormone production can result in some disorders in body such as nervousness, muscle weakness, unexplained weight loss, sleep disturbances and vision problems. Based on the surveys, 20 billion people suffer from thyroid swelling or thyroid cancer. To earlier prevent and find out the condition of its thyroid gland, a diagnosis is needed regarding this disease. Useful knowledge can be extracted from the database where a significant amount of relevant data is stored. Some studies related to how to diagnose thyroid conditions can be done by studying the image from the thyroid data itself. Some that can be done are image processing and classification. One of the studies that have been done is Waheed (2017) with a new decision-based hybrid system, the proposed system consisting of three stages.

In the first stage, 25 features of the dataset (retrieved from the University of California Irvin machine learning repository) were reduced using Information Gain method to avoid data redundancy and reduce computation time. In the second stage, the missing values in the dataset are dealt with k-Nearest Neighbor (k-NN) weighting pre-processing scheme. Finally, the resultant data was provided as input to Adaptive Neuro-Fuzzy Inference System for the purpose of input output mapping in the last stage for system [40], the classification accuracy for the Information Gain Adaptive Neuro Fuzzy Inference System (IG-kNN-ANFIS) to diagnose thyroid disease was calculated as 99.1%, as the highest accuracy ever recorded compared to Hui-Ling et al. (2012) using FS-PSO-SVM reaching only the accuracy of 98.59.

Research conducted by Soumya et al. (2015) [41] proposed an automatic classification for kidney diseases in ultrasound image. The classification was divided into four types: Normal, Cyst, Renal Failure and Angiomiolipoma. The features used were the statistical features and set of multi-scale wavelet-based features taken from the ROI of the test image. The PCA was then used to reduce the number of features. ANFIS was used as a classifier with two hidden layers, each of which contained 10 neurons and five output nodes. A Sanger's rule and sigmoid activation function were used in the ANFIS learning process. The tolerance limit for errors used (a mean square error) was 0.05 for the end of learning limit. The results showed the correct classification rate reaching 92% using multi-scale wavelet-based features

IV. Conclusion

In this work, we present a review about the hybrid method called as ANFIS in the medical image area. In this review, ANFIS was used as a classifier in the model proposed in the reference of this research. Overall, ANFIS was able to give a satisfying result in comparison to other methods in the test. The learning ability owned by neural network, the existence of a set of rules and an inference method combined in a connected structure could make this method able to adapt in a set of dataset given. However, the research results that have been reviewed from a number of reference sources showed some drawbacks in this method. The more number of data inputs could reduce the accuracy of the performance of this method. Conversely, the ANFIS performance would be improved with the sufficient number of input samples and the addition of the nodes in the hidden layer of ANFIS. However, it certainly takes more time for computation. In general, the performance of classifier would be dependent upon several factors such as size and quality of training set, the imported training rigor and parameters chosen to feed to ANFIS as the inputs can affect the classifier performance.

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