Malaysian Journal of Computing, 3 (1): 54–66, 2018

eISSN: 2600-8238 online

CLASSIFICATION OF PADDY WEED LEAF USING NEURO-FUZZY METHODS

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ABSTRACT

Paddy weed appears to be one of the many visible threats to paddy crop production and subsequently farmers' income. It is for this reason that the growth of paddy weeds in paddy fields should be controlled as it results in a significant decrease of paddy yields. However, farmers might have limited knowledge on weed types, and are thus unable to identify and determine the right prevention methods. This paper presents classification methods for paddy weeds through the leaf shape extraction and applies neuro-fuzzy methods for recognizing the types of weeds. The types being focussed are the Sphenoclea zeylanica, Ludwigia hyssopifolia and Echinochloa crus-galli. The developed e-prototype methods would be able to classify paddy weeds with 83.78% accuracy. Hopefully, the findings in this study would assist farmers and researchers in increasing their paddy yields and eliminating weed growth respectively. The production of paddy in Malaysia would eventually be improved with the proposed methods, which can be considered as a technology advancement in the field of paddy production.

Keywords: *Classification, Image Processing, Neuro-Fuzzy, Paddy Weeds, Shape*

1. Introduction

Rice is the highest quantity of food grain which is consumed by nearly 50% of the world's population (Kwak *et al.*, 2008). In Malaysia, paddy is a staple food, such that it is important to manage the crops for food security and the economy. Up until now, many researches have been conducted to increase paddy production in Malaysia such by introducing new varieties of paddy and aerobic paddy, which uses less water. These varieties are being planned mainly by the Malaysian Agricultural Research and Development Institute (MARDI). However, there is a threat to the paddy fields which is the widespread growth of weeds, which in turn will increase paddy yield loss. The worldwide rice yield loss caused by paddy weeds is almost ten percent (Rabbani *et al.*, 2011). This is because these weeds compete with paddy for nutrients, water and sunlight (Hakim *et al*., 2011).

Although the growth of paddy weeds can be reduced by using herbicides, if it is done at too late a stage, the paddy yields in terms of both quantity and quality may be adversely affected. Moreover, some of the farmers may lack the necessary knowledge in weed control and they do not know the paddy weeds' habitat before buying the herbicides. Determining weed types could be confusing due to its similar features and characteristics to paddy and other weeds. Consequently, the use of herbicides on the crops has become ineffective. Herbicides may help in killing the weeds and in order to find the best herbicides, farmers do not mind paying high cost with a perception it is effective. However, the weeds can take quite a long time to die after being sprayed with herbicides. If the weeds are being sprayed frequently with same type of herbicide, the weeds can also become immune.

Therefore, it is important for paddy farmers to identify the weeds in their paddy fields to resolve the problem effectively. The proposed prototype method is expected to assist farmers in recognizing paddy weeds using captured images that tend to be far more accurate. The prototype is developed and tested using machine learning approach. For further explanation, this paper is organized into five sections. It begins with the introduction and some related works on paddy weeds. Subsequently, the material and methods are described. This is then followed by the results and discussion and finally, the paper ends with some conclusions.

1.1 Paddy Weeds

Basically, there are three types of weeds which are sedges, grasses and broadleaved weeds. Hakim *et al*. (2011) stated that paddy loss caused by weeds might be in different forms depending on where the weeds are found. It also depends on the predominant flora and the control techniques used by paddy farmers. These weeds need to be dealt with quickly especially in the early stages to prevent paddy loss (Dangwal *et al*., 2012). In Malaysia, researches are focused on improving the farmers' weed control management such as developing a better breed of rice paddy and enhancing the current herbicides (Abdul Shukor *et al*., 2013; Rahman *et al.* 2012). However, these methods are appropriate only if farmers recognize the type of weeds found in their fields and apply the right herbicides.

There are several locations in Malaysia that have been identified with having among the highest growth rate in paddy weeds in the fields. These locations are in Tanjong Karang, Selangor (Hakim *et al*., 2011), Kuala Muda, Kedah (Mashhor Mansor *et al*., 2012) and Seberang Perak, Perak (Hakim *et al*., 2013). Based on these studies, the most common paddy weeds found in Malaysia are the Echinochloa crus-galli, Ludwigia hyssopifolia and Sphenoclea zeylanica. Further information is provided below and in Table 1.

1) Echinochloa crus-galli: According to Man *et al*. (2015), Echinochloa crus-galli or "Rumput sambau" is from the poaceae family. The length of its leaf is between 8 to 60 centimetres long. The leaf is glaborous or hairless. It can be controlled chemically by using chemicals such as molinate or quinclorac.

2) Ludwigia hyssopifolia: Man *et. al*. (2015) stated that Ludwigia hyssopifolia is from the onagracae family. In Malay, it is called "maman pasir". The lance-shaped leaf is between 2 to 10 centimetres long. The treatment for this type of weed is by using chemicals such as glufosinate ammonium or glyphosate, if it grows on the edge of the paddy fields. If the weeds are within the field, chemicals such as 2,4-D or cyclosulfamuron is normally recommended.

3) Sphenoclea zeylanica: Sphenoclea zeylanica or commonly known as "cabai kera" in Malay, originates from the spenochleaceae family (Man *et al*., 2015). Its leaf can grow up to 10 centimetres long and it is usually oblong or lance-shaped. In order to control it, chemicals, such as bensuronmethyl is recommended to be used in the fields.

Table 1. Characteristics of Paddy Weeds

Plant Name	**Echinochloa crus-galli**	**Ludwigia hyssopifolia**	**Sphenoclea**
Family	Poaceae	Onagraceae	Sphenocleaceae
Life Cycle	Annual	Annual	Annual
Propagation	Seeds	Seeds	Seeds
Height	Up to 200 cm tall	15- 150 cm tall	7 – 150 cm tall
Leaf Length	8 – 60 cm	2 – 10 cm	Up to 10 cm
Leaf Shape	Hairless	Lance-shaped	Lance-shaped

Throughout the literature review, there are also several other countries that are facing weed problems like Cambodia, Indonesia and India. Different countries have different types of weeds due to differences in climate and seasons. The rate of growth of the paddy weeds can also be affected by these differences. In order to develop a prototype that is able to recognize paddy leaves, we explore several techniques available for the learning process, coupled with methods of image processing.

1.2 Back Propagation Neural Network and Fuzzy Logic

Back Propagation Neural Network (BPNN) is one of the Artificial Neural Network (ANN) algorithms used for classification. According to Husin *et al*. (2012), BPNN is the easiest algorithm to understand and has the lowest computational time. It is a feedback method where the algorithm computes the error from the training epochs. These errors are then used to adjust the weight of each of the nodes in the inputs and the hidden layers. Once the training phase has been done and the weights have been adjusted to reduce the errors, the testing phase is executed to verify the accuracy of the system. The errors and the accuracy of the system rely on several factors~~,~~ such as the split ratio for training and testing set, the number of epochs used and the learning rate. Several researchers have applied this algorithm which has been proven to obtain high accuracy such as bankruptcy prediction (Lee and Choi, 2013) and glaucoma identification (Samanta *et al*., 2015).

The fuzzy logic system is a set of members with a degree of membership between 0 and 1. This system is based on the human-like knowledge and representation of certain characteristics of the objects. The system is the opposite of classical sets where it contains either 0 or 1 on every element (Dubey *et al*., 2013). The linguistic variables are based on natural human expressions on certain objects. There are different types of fuzzy inferences for the evaluation of the membership values such as Mamdani, Sugeno and Takagi-Sugeno-Kang method. The main advantage of using the fuzzy logic system is that it can determine the fuzzy values of each member in the objects.

The neuro-fuzzy system has overcome the limitations of ANN and fuzzy inference system. Fuzzy inference system does not have the ability to learn while ANN is unable to determine the uncertain~~ty~~ values of the variable. This system incorporates the computation for uncertainties and learning capabilities of ANN with the human-like knowledge and representation of the fuzzy inference system. Therefore, ANN is becoming more transparent with membership function in the hidden nodes and fuzzy inference system is able to learn. Cotton plant disease has captured the attention of several researchers who proposed the application of the Adaptive Neuro-Fuzzy Inference System for recognizing different diseases, which might be hardly observed by the human eye (Rothe and Kshirsagar, 2015; Shanoor *et al*., 2016).

In our research, leaf images are the source of information and are being used to train the neuro-fuzzy classifier. The common shape features of the leaf are the length, width, area and perimeter. These features can be extracted by processing the Canny edge detection, binarization and others. Some images are divided into sets of ratio segments to improve the accuracy of the system. The shape features were also used by (Chaki & Bhattacharya, 2015). Chaki & Bhattacharya (2015) proposed the neuro-fuzzy classifier, and in order to test the accuracy of the system, they compared it with the Neural Network and k-Nearest Neighbour classifiers. The study analysed 640 images of leaves to classify them into 32 predefined classes. The leaves were subjected to the image pre-processing steps. Firstly, the scale and the orientation of the images transformed in same standardization and later the computation of the shape features is done. Images were converted into binary form. The angle of the major axis, which is the length of the leaf was oriented/placed horizontally. Next, the background was cropped until the leaf fits within the boundary of the rectangle. The images also were scaled into pre-defined sizes called “segments” according to the aspect ratio values of the leaves. Based on these workflows, we adapted the similar steps and further adaption is discussed in the next section.

1.2 Feature Extraction

Simply defined, the process of transforming the inputs or raw data into a set of features is called feature extraction (FE). A review on FE in image processing can be found in Kumar and Bhatia (2014), where several FE techniques were reviewed and some problems were highlighted.

Classification of paddy weed leaves deals with feature extraction (FE) methods. FE methods have become an important pre-processing method, as the weed leaves in its natural form (i.e. image) has to be extracted prior to building the neuro-fuzzy model. FE describes the meaningful information contained in a pattern to ease the pattern recognition process. It is regarded as a feature transformation or sometimes can be considered as a dimensionality reduction process. The main aim is to have a meaningful representation for an algorithm to process in order to get the insightful/relevant/necessary knowledge/information. If the set of features is carefully selected, the classification process becomes faster, which in turn can improve the modelling process.

Numerous image pre-processing techniques like binarization, thresholding, resizing and normalization have been widely applied in many studies (Abd. Razak *et al*., 2017, Shamsuddin *et al*., 2017, Anjomshoae & Rahim, 2018). The use of feature extraction techniques was applied in Abd. Razak *et al.* (2017) in which the color of the paddy leaves was first divided into four groups of colors based on the Leaf Color Chart (LCC). The color group is then extracted based on the gradient scale of grayscale, and these features were then used to identify the optimum amount of nitrogen fertilizer for paddy fields. Anjomshoae and Rahim (2018) performed several feature extraction techniques on hevea leaves or rubber tree to identify the clone types. In their studies, they proposed the key point extraction and line detection method to extract shape and axil or angel of leaflet position. Several key points extraction methods like SIFT, Harris and FAST were compared and their results showed that the key point extraction method helps to extract more meaningful features. In another study by Shamsuddin *et al.* (2017), cascade detector, cropping, resize were some of the feature extraction techniques used to extract the features from the eye images.

2. Materials and Methods

This section delivers the key approaches by first~~;~~ taking the raw image (data) and performing several image pre-processing techniques such as cropping and rescaling. Next, each of the images was then processed through conversion into grayscale and binary form to extract the features of the leaf. Later, the features extracted were used and discretised in Weka before rules generation are done and presented in fuzzy rule based. Finally, the neuro-fuzzy system will determine the type of the paddy weed based on the features of the leaf.

Images of the paddy weeds were obtained from paddy fields in locations such as Seberang Perai, Pulau Pinang and Sungai Besar, Selangor. Apart from the locations, we downloaded files from Pl@ntNet, a repository of images of paddy weeds. The data obtained was in the Portable Network Graphics (PNG) format due to its lossless data characteristics. For this experiment, we have collected 248 samples of leaves in total. Figure 1 shows the examples of the images obtained and Table 2 shows the number of samples collected.

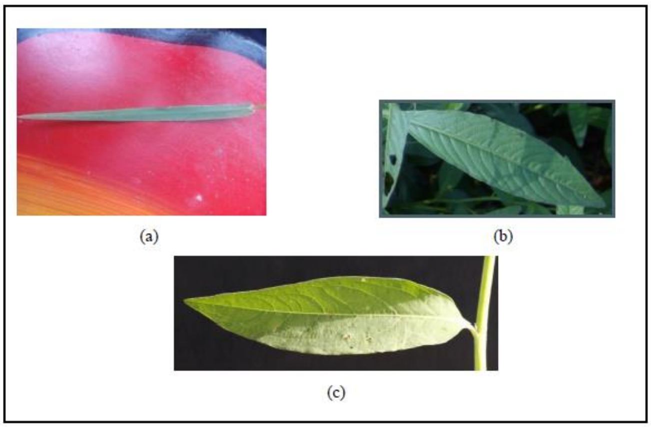

Figure 1. Examples of images of paddy weed leaves (a) Echinochloa crus-galli (b) Ludwigia hyssopifollia (c) Sphenoclea zeylanica

Table 2. Number of samples of paddy weeds

Plant weed type	**No. of samples**
Echinochloa crus-galli	48
Sphenoclea zeylanica	100
Ludwigia hyssopifolia	100

2.1 Image Processing

The images from the public repository are of different sizes. In addition, the images have background colour that should be removed. We applied several image processing methods such as orientation, cropping and scaling conversion on the images. The methods were used to ensure that the images were aligned uniformly and the feature values extracted made more accurate. Firstly, image orientation was done to set the image of the leaf horizontally. Next, cropping process was done to remove unnecessary spaces from the image for more accurate measurement. Finally, scaling was done to minimize the size of the image and maintain the image of the leaf. Once the image processing has been done, the images are then converted into black and white images. These steps are crucial so that the features of the leaf can be extracted effectively. Figure 2 shows the flow of the image processing techniques involved while Table 3 shows the ratio, *R* which is equal to the length of the image, *l*, divided by the width of the image, *w* and the rescaling process in pixels.

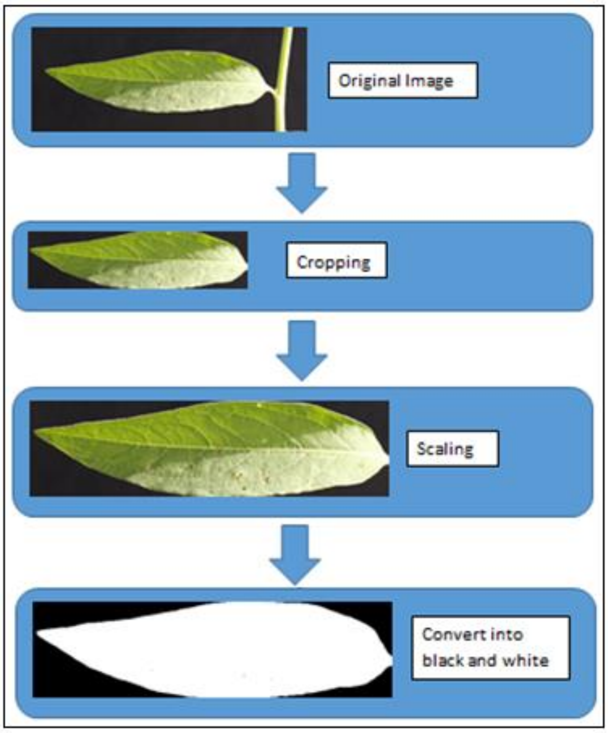

Figure 2. Workflow of image processing from the original image to a black and white image

Table 3. Ratio and scaling dimension of image

Ratio, *R*	**Dimension of image (*l*w*)**
R <= 1.4	300 x 300
1.4 < R <= 2	300 x 200
2 < R <= 2.4	200 x 140
2.4 < R <= 3	200 x 100
3 < R <= 3.5	300 x 65
R > 3.5	400 x 45

2.2 Feature Extraction

There are four fuzzy variables for this study, which are length (l), width (w), perimeter (p) and area (a) that resemble~~s~~ the shape of the leaf~~,~~ as shown in Table 4. The length and width features are then calculated using Equations (1) and (2) below:

Length, $l = b - a$ (1)

Width, $w = d - c$ (2)

a is the column value where the first white pixel is detected starting from the left side, and b is the column value where the first white pixel is detected starting from the right side. c is the row value of the first white pixel found starting from the bottom and d is vice-versa. Perimeter is determined by calculating the number of white pixels that form an outline of the image. Area of the image is determined by calculating the white pixels within the closed contours. The number of samples retrieved for the experiment is shown in Table 4, together with the minimum, maximum and average values of l, w, p and a for each species.

Table 4. Number of Samples in Dataset

Plant weed	Echinochloa crus-galli	Ludwigia hyssopifolia	Sphenoclea zeylanica
No. of Samples	48	100	100
Min Length	358	174	175
Max Length	390	277	293
Mean Length	379	237.5	268
Min Width	11	58	29
Max Width	18	281	275
Mean Width	18	210	165
Min Perimeter	739.782	450.818	453.747
Max Perimeter	809.238	950.164	904.715
Mean Perimeter	783.0245	896.779	795.231
Min Area	1496.5	7683.5	5760
Max Area	3567.5	42018.5	24706
Mean Area	3458	27354.5	16292.75

The samples were analysed by using discretization filter in WEKA 3.9 and the function helps to identify the membership functions of length, width, perimeter and area variables. Discretization is done by dividing the value of the variable into 3 bins for each of the variable namely small or short, medium and long or large. The membership functions of the variables are shown in Table 5, which are calculated by determining the minimum and maximum value of each bin which intersects with one another. After the discretization process, a decision table is created as a tool to generate rules. The rules are based through the observation and analysis of the images. We created several rule-sets to generalise the type of weeds. The rules are generated to sets of 12, 24, 36 and 48 prior to accuracy testing and visualized in Figure 4.

Table 5. Membership Functions of Fuzzy Variables

Fuzzy Variables	Fuzzy Values		
	Short (variables *l* and *w*) Small (variables *p* and *a*)	**Medium**	**Long (for *l* and *w*) Large (for *p* and *a*)**
Length (*l*)	0 – 200	100 – 300	200 – 400
Width (*w*)	0 – 150	100 – 250	200 – 300
Perimeter (*p*)	0 – 600	300 – 900	600 – 1200
Area (*a*)	0 – 20000	10000 – 30000	25000 - 50000

By observing the data and the graph of each bin for every variable, the rules were generated based on the rules of thumb. For example, Echinochloa crus-galli has the highest readings when the length is long, width is short, perimeter is medium and the area is small. Therefore, the rule generated is:

"IF length = long AND width = short AND perimeter = medium AND area = small THEN plant weed = Echinochloa crus-galli"

A total of 48 rules were generated and the highest membership function of each variable is prioritized to be selected for the rules generation. If the rules have been generated using the same membership function, then the second highest function is selected. The unit measurements of the variables are in pixels.

Length, Width \ Perimeter, Area	S,S	S,M	S,L	M,S	M,M	M,L	L,S	L,M	L,L
S,S	A	A		A	A				
S,M		A		A	A	B		B	B
S,L				B	B	B		B	B
M,S	A	A		B	C	C	C	C	
M,M	A	A		A	B	B	C	C	B
M,L	A	A			B	B		B	B
L,S				C	C	C	C	C	
L,M	A	A		C	C	C	C	C	
L,L									

= 12, 24, 36, 48 rules (red)
= 24, 36, 48 rules (orange)
= 36, 48 rules (green)
= 48 rules (blue)

A = *Sphenoclea zeylanica*
B = *Ludwigia hyssopifolia*
C = *Echinochloa crus-galli*

Figure 3. Rules generation based on feature extraction

Several samples of rules are listed as below:

- Rule 1: IF Length is Short AND Width is Short AND Perimeter is Small AND Area is Small THEN Paddy Weed is Sphenoclea zeylanica
- Rule 10: IF Length is Medium AND Width is Medium AND Perimeter is Small AND Area is Small THEN Paddy Weed is Sphenoclea zeylanica
- Rule 20: IF Length is Short AND Width is Long AND Perimeter is Medium AND Area is Small THEN Paddy Weed is Ludwigia hyssopifolia
- Rule 38: IF Length is Medium AND Width is Medium AND Perimeter is Large AND Area is Medium THEN Paddy Weed is Echinochloa crus-galli

2.3 Architecture Design

Generally speaking, a neuro-fuzzy model has input, output and three hidden layers which represent the membership functions and fuzzy rules (Borah *et al*., 2015). The architecture of the neuro-fuzzy model accepts four input variables and the engine will extract them from the given images. Therefore, the neuro-fuzzy model incorporates the computation and learning capabilities of ANN with the human-like knowledge and representation from the fuzzy logic system. Figure 5 shows the neuro-fuzzy architecture that was designed for this study.

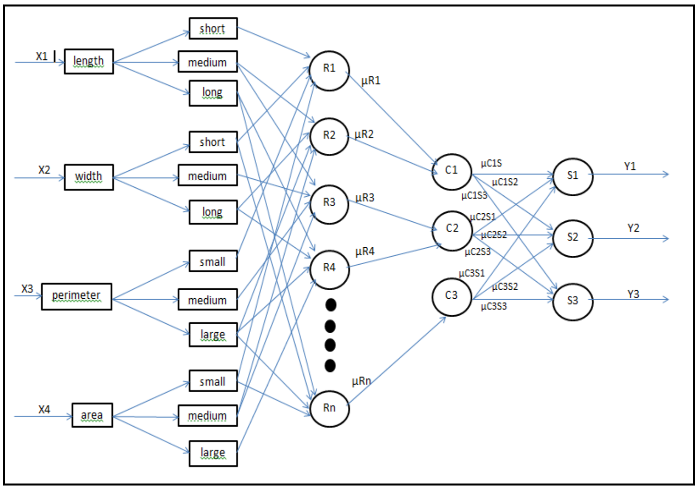

Figure 5. Neuro-fuzzy architecture

The first layer retrieves the crisp value of the data, which were obtained from the feature extraction phase. The second layer fuzzifies the crisp value into fuzzy set value. The fuzzy value is used for evaluating the rules on the next layer. The third layer evaluates the rules based on the fuzzy value given. The membership values of each rule is determined. Variable *xi* is the crisp value of the features of the leaves, which is the input for the system. Variable *Si* is the value of the output node.

The fourth layer combines all the values of each rule into a single fuzzy value. Rules with the same output is combined to produce a single value of the specified output. The fifth layer compares the fuzzy values of each node and defuzzifies the value to produce a single crisp output, which is the type of the weed. In the fourth layer, the combination is done by using the probabilistic OR, which is calculated using the formula in Equation (3):

$$C\mathrm{m} = \Sigma(Ri*\mu Ri) - ((R0*\mu R0)*(R1*\ \mu R1)*\ldots*(R(n-1)*n-1i=0\ \mu R(n-1))) \quad (3)$$

where,

Cm = aggregated membership value of output *m*

Ri = membership value of output for rule *i*

n = number of rules

m = number of hidden node

C is the fuzzy value according to the combined values from the rules that were related to it, *R*. Throughout the model, weight is set in the third and fourth layers for the learning capabilities. Mean squared error is also calculated to adjust the weight of the nodes in the input, hidden and outer layer much like the standard BPNN system. Sigmoid function is used as the activation function because the value used in the model is continuous.

In order to evaluate the neuro-fuzzy model, the hold out method is implemented to calculate the mean error of the testing sets, which determines the accuracy of the model. The data was split into two sets, training and testing set. Different split ratios used are 60:40, 70:30 and 80:20. The learning rate was set from 0.5 to 1. The number of epochs ranged from 200,000 to 1,000,000 with 200,000 intervals. The training process starts by receiving the image data measurements, which are length, width, perimeter and area in the excel file format (.csv). Since we have designed four fuzzy rules sets, we also have to carry out four training cycles with three split ratios of datasets. We recorded the accuracy of each fuzzy rules set for the purpose of evaluation.

3. Results and Discussions

As the prototype was successfully developed, it was tested for its correctness in classifying the paddy weeds. The testing data was in the form of excel data file (.csv) which contains the measurements of the leaf. The accuracy of the model is calculated using the formula in Equation (4):

$$Accuracy = \frac{\#ofcorrect}{\#ofsamples} * 100\% \tag{4}$$

Firstly, we evaluated the different sets of rules. It is based on the average training and testing accuracy of each number of rules. Based on Table 6, it is shown that higher set of rules produce lower mean squared error for three different datasets, Dataset 1 (60:40), Dataset 2 (70:30) and Dataset 3 (80:20). The lowest average mean squared error for these datasets were 0.002181, 0.002557 and 0.002521 respectively when using 48 rules. By using 48 rules, the next experiment was carried out to identify the optimal learning rate for each dataset. In this experiment, it is shown that Dataset 1 has the lowest average mean squared error when the learning rate is 0.7 with 0.001928. However, Datasets 2 and 3 have the lowest average MSE when the learning rate is 0.9 with 0.00221 and 0.002064 respectively. Table 7 shows the results of the all the datasets on different learning rates.

Table 6. Average MSE on Different Datasets and Number of Rules

	Average Mean Squared Error			
Dataset	**12 Rules**	**24 Rules**	**36 Rules**	**48 Rules**
1 (60:40)	0.005544	0.004809	0.003952	0.002181
2 (70:30)	0.004887	0.004377	0.003499	0.002557
3 (80:20)	0.004921	0.004131	0.003735	0.002521

Table 7. Average MSE on Different Learning Rates

	Average Mean Squared Error		
Learning rate	**Dataset 1**	**Dataset 2**	**Dataset 3**
0.5	0.002506	0.002912	0.003048
0.6	0.002364	0.002488	0.002620
0.7	0.001928	0.002516	0.002378
0.8	0.002366	0.002548	0.002155
0.9	0.001938	0.002210	0.002064
1.0	0.001986	0.002668	0.002372

Besides the average mean squared error, testing accuracy was calculated as well. For Dataset 1, the best learning rate is 0.5 while Datasets 2 and 3 are 0.6 and 0.8 respectively. Figure 5 shows the graph of the average accuracy based on learning rates.

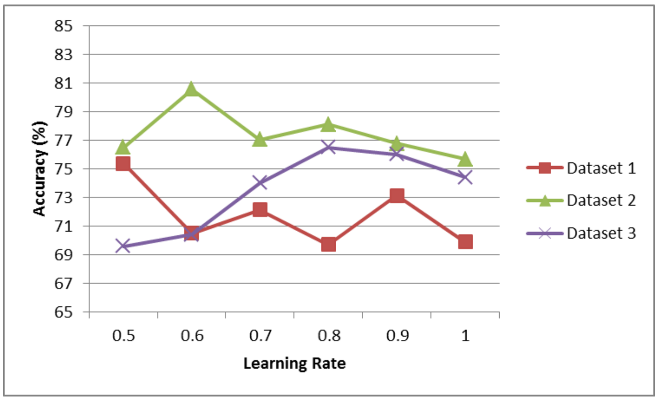

Figure 4. Average accuracy of learning rate on different datasets

Using the optimal learning rate for each dataset as mentioned above, the number of epochs is tested for better accuracy. The number of epochs ranged between 200,000 and 1,000,000 epochs.

Based on the experiment, Dataset 1 has the highest accuracy using 200,000 epochs, while Datasets 2 and 3 iterated 1,000,000 epochs to gain the highest accuracy. The final results of the experiment show that by using the optimal parameters for each dataset, the accuracy of Datasets 1, 2 and 3 are 78.79%, 83.78% and 82% respectively. Table 8 shows the optimal parameters for each dataset and their results.

Table 8. Optimal Parameters of Datasets

Dataset	1	2	3
Learning Rate	0.5	0.6	0.8
Number of epochs	200,000	1,000,000	1,000,000
Mean Squared Error	0.0036	0.00173	0.0016
Accuracy (%)	78.79	83.78	82

4. Conclusions

This study carried out analysis in the construction of fuzzy sets and neuro-fuzzy architecture. We constructed the fuzzy rules and later tested the rules in the architecture. The developed prototype was able to classify the paddy weeds through the shape of the leaves based on features such as length, width, area and perimeter extracted from the images. With the highest accuracy of 83.78%, this prototype can be considered reliable and efficient. It is our hope that the prototype can help paddy farmers take quick actions to identify the weeds, and later know how to deal with the weeds (e.g. deciding on the right herbicides) in their paddy fields. However, there are several limitations in the study, which can be considered in future enhancements/research such as the environmental conditions during image capturing and~~,~~ also consider advance devices to be integrated.

Acknowledgement

The authors would like to express their gratitude to all related parties, experts from MARDI, Kepala Batas and also to IRMI UiTM, Shah Alam for REI 19/2015 for the grant received.

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