Fish swarm intelligent to optimize real time monitoring of chips drying using machine vision

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Abstract. This study attempted to apply machine vision-based chips drying monitoring system which is able to optimise the drying process of cassava chips. The objective of this study is to propose fish swarm intelligent (FSI) optimization algorithms to find the most significant set of image features suitable for predicting water content of cassava chips during drying process using artificial neural network model (ANN). Feature selection entails choosing the feature subset that maximizes the prediction accuracy of ANN. Multi-Objective Optimization (MOO) was used in this study which consisted of prediction accuracy maximization and feature-subset size minimization. The results showed that the best feature subset i.e. grey mean, $L_{(Lab)}$ Mean, $a_{(Lab)}$ energy, red entropy, hue contrast, and grey homogeneity. The best feature subset has been tested successfully in ANN model to describe the relationship between image features and water content of cassava chips during drying process with R^2 of real and predicted data was equal to 0.9.

1. Introduction

Drying is a vital postharvest process for most agricultural products [1]. The most important processes in flour processing Modified Cassava Flour (MOCAF) is upon drying. Artificial drying is suggested to use due to many advantages such as drying temperature and air flow can be set so that drying process is more quickly and evenly and hygiene materials are also more awake. Aghbashlo et al. [2] uses machine vision method for real time monitoring of food quality during the drying process and found that this method is suitable for observing the changes in the mechanical, sensory and nutritional food. With the existence of this monitoring system, the better characteristic parameters of process at the time of drying and quality evaluation can be achieved. Dutta et al. [3] presented a computer vision based non-destructive method to identify the presence of acrylamide in potato chips with the results have shown accuracy over than 94%. Baigvand et al. [4] observed the used of machine vision system for grading of dried figs and achieved accuracy up to 95.2%. Benalia et al. [5] developed automated systems based on computer vision to improve the quality control and sorting of dried figs. Using models of CIE XYZ, CIELAB, and Hunter Lab colour spaces, in term of the browning index measurement of each fruit by accuracy of 99.5%. Yadollahinia and Jahangiri [6] developed a thin-layer dryer with machine vision system using image processing software for potato slice and shown that the system successfully effective to monitor the shrinkage of potato slice during drying.

In agricultural and biological engineering, researchers and engineers have developed methods such as artificial neural network (ANN) to analyse the operation of food processing [7]. Khazaei et al. [8] presented a new method for predictive modelling of grape drying process for on-line monitoring and controlling of this process. In the area of food quality control, ANN has been successfully applied to predict the quality of agricultural raw material [9-11]. Azadbakht et al. [12] investigated the application of ANN in intelligent drying process to energy analysis of fluidized bed dryer for potato cubes. A large share of energy utilization in the food industry.

Feature selection entails choosing the feature subset that maximizes the prediction accuracy of ANN. Features which do not appear relevant singly may become highly relevant when taken with others [13]. Many studies have proved the benefit of using nature inspired algorithms for feature selection techniques [14-18]. Hendrawan and Al Riza [19] has successfully implemented fish swarm intelligent (FSI) to select relevant features as the input of ANN to predict water content of a plant. The objectives of this study were modelling image features to predict the water content of cassava chips during drying by using ANN and optimizing the feature selection technique to select relevant image features subset by using FSI.

2. Materials and Methods

2.1. Materials and equipment

Five hundred samples of cassava chips in various water contents were used. As a mean of manipulating their physiological status, the samples were subjected to different water states. Water states was determined by drying the sample at 70°C in tray dryer. Water status was defined as the average amount of water available for each sample of data acquisition in percentage of its initial dry weight [20]. The drying experiments were performed in a tray dryer as shown in Figure 1, which can be controlled for drying in the temperature range of 50-70°C. Prior to starting of each experiment cassavas were washed, peeled, and sliced into chips of 1 mm thickness with a mechanical slicing machine.
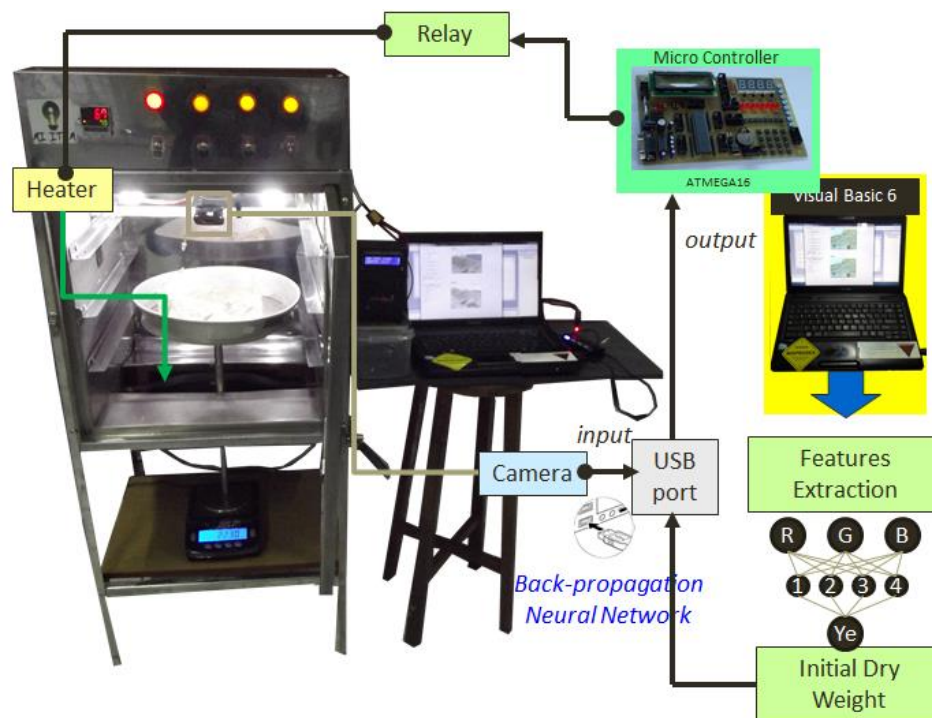

Figure 1. Modified tray dryer using computer vision

2.2. Model of study

First process was image acquisition, in which the cassava chip images were captured using digital camera (Logitec HD Webcam C270, Japan) placed at 300 mm perpendicular to the sample surface and connected to the USB port of a computer with Intel core i7 processor. The digital camera was used for image acquisition which provides images in BMP format. Images were captured with its maximum resolution (1280 x 720). Imaging was done under controlled and well distributed light conditions. Light was provided by two 22W lamps (EFD25N/22, National Corporation, Japan). Light intensity over the cassava chip surface was uniform at 300 lux in the centre of the region during image acquisition. During drying image of the cassava chips were captured continuously by computer vision system. After drying had finished, total of 500 image data which varies at different water contents were acquired. Image analysis was performed according to a software specially developed for this purpose using Visual Basic 6.0. Image features which consist of colour features (CFs) and textural features (TFs) were extracted from each image data. Modelling was done using back propagation neural network (BPNN) to describe the relationship between image features (CFs and TFs) and water content of cassava chip. Selection process for selecting relevant image features was done using nature-inspired approaches *i.e.* FSI. Multi objectives optimization (MOO) concerns optimization problems with multiple objectives [21]. The fitness was calculated using equation 1, 2, and 3 where $MSE_{(x)}$ is the mean square error of validation-set data of BPNN using only the expression values of the selected image features in a subset x, where $IF_{(x)}$ is the number of selected image features in x. f_t is the total number of image features, $weight_1$ and $weight_2$ are two priority weights corresponding to the importance of the accuracy and the number of selected image features, respectively, where $weight_1 =$ 0.6 and $weight_2 = 0.4$. In this study, the accuracy was more important than the number of selected image features in a feature-subset.

$$function_1 = weight_1 \times MSE_{(x)} \ (1); \ function_2 = weight_2 \times \frac{IF_{(x)}}{f_t} \ (2); \ fitness\,(x) = function_1 + function_2 \ \ (3)$$

2.3. Colour features (CFs)

CFs include colour mean value which can be described according to equation 4 [22] where: colour value can be defined as the range of each colour space in the pixel *i.e.* red, green, blue, grey, hue, saturation$_{(HSL)}$, saturation$_{(HSV)}$, lightness$_{(HSL)}$, value$_{(HSV)}$, $X_{(XYZ)}$, $Y_{(XYZ)}$, $Z_{(XYZ)}$, L, $a_{(Lab)}$, $b_{(Lab)}$, $C_{(LCH)}$, $H_{(LCH)}$, $u_{(Luv)}$ and $v_{(Luv)}$. M is the total number of pixels in the image. The total number of CFs are 19 features.

$$colour \ mean \ value = \frac{1}{M} \sum_{i=1}^{M} colour \ value$$
$$(4)$$

2.4. Textural features (TFs)

The textural analysis can be considered as one of applicable techniques for extracting image features [23]. The Colour Co-occurrence Matrix (CCM) procedure consists of three primary mathematical processes: (1) the image is transformed from RGB colour representation to other colour representation such as grey [24], HSL and HSV [25], Lab and XYZ [26], LCH [27] and Luv [28]; (2) generation of Spatial Gray-Level Dependence Matrices (SGDMs) [29], resulting in one CCM for each colour space, the CCM was calculated based on normalization value; and (3) determination of ten Haralick Textural Features [17]. Based on the results of preliminary observation in various combination of angle ($\theta = 0$, $\theta = 45$, $\theta = 90$, $\theta = 135$) and distance ($d = 1$, $d = 2$, $d = 3$), it was showed that combination of angle ($\theta = 0$) and distance ($d = 1$) performed better than the other combination of θ and d to identify cassava chip water content. Therefore, in this study, TFs were extracted at those values of θ and d. A total of 190 TFs were extracted *i.e.* 10 TFs each for R, G, B, grey, hue, saturation$_{(HSL)}$, saturation$_{(HSV)}$, lightness$_{(HSL)}$, value$_{(HSV)}$, $X_{(XYZ)}$, $Y_{(XYZ)}$, $Z_{(XYZ)}$, $L_{(Lab)}$, $a_{(Lab)}$, $b_{(Lab)}$, $C_{(LCH)}$, $H_{(LCH)}$, $u_{(Luv)}$, $v_{(Luv)}$. Therefore, the total image features (f_t) which were extracted from both CFs and TFs are 209 features.

2.5. Fish swarm intelligent (FSI)

The steps of the proposed FSI [30] were as follows: (1) initialisation of FSI parameters. The maximum iteration was 500. The number of fish population (N_{fish}) was 70, the crowded parameter (C_p) was 0.3 and the leaping value (*leap*) was 10 based on the results of preliminary runs; (2) generated the location of each fish randomly [0, 1] (e.g. *fish$_i$*: 0,1,1,0,0,0,0,1,0,0,1,0,..... f_t); (3) evaluated the fitness of *fish$_i$* using MSE of BPNN; (4) updated the individual solution *F(fish$_i$)*; (5) found the best solution (*fish$_{best}$*); (6) calculated visual scope (*vis$_{scope}$*) using equation 5 and 6; (7) calculated central point of the population (*cent$_{point}$*) using equation 7 and 8, e.g. *cent$_{point}$*: 0,0,0,1,1,0,0,1,0,0,.......f_t; (8) repeated steps 8.1 to 8.4 for those *fish$_i$* with partial solutions; (8.1) if the visual scope of *fish$_i$* was empty (*vis$_{scope}$ = 0*) then *fish$_{i+1}$* would generate its location randomly. Otherwise it went to *condition1*; (8.2) *Condition1*: If the visual scope of *fish$_i$* was crowded (*vis$_{scope}$ > C_p*) then *searching* which means *fish$_i$* will generate random location *fish$_{rand}$*. If *F(fish$_{rand}$)* was better than *F(fish$_i$)* then there would be a two points crossover process between *fish$_{rand}$* and *fish$_i$*. Otherwise it went to *condition2*; (8.3) *Condition2*: 1th *process*: If the *F(cent$_{point}$)* was better than *F(fish$_i$)* then *swarming* which means there would be a two points crossover process between *cent$_{point}$* and *fish$_i$*, but if the *F(cent$_{point}$)* was not better than *F(fish$_i$)* then *searching*. The output of the 1st *process* was *fish$_{y1}$*. 2nd *process*: If the *F(fish$_{best}$)* was better than *F(fish$_i$)* then *chasing* which means there would be a two points crossover process between *fish$_{best}$* and *fish$_i$*. But if the *F(fish$_{best}$)* was not better than *F(fish$_i$)* then *searching*. The output of the 2nd *process* was *fish$_{y2}$*; (8.4) updated *vis$_{scope}$*, *cent$_{point}$* and *fish$_{best}$* using equation 9; (9) If the *F(fish$_i$)* equal to *F(fish$_{i+1}$)* then updated the *leap* factor. If the *leap* factor reached the threshold point (*leap = 10*), then *fish$_{i+1}$* would move randomly; (10) updated the best feature-subset; (11) the search would terminate if the maximum iteration had been reached.

$$M = \left[M_{jk} \right] = \frac{\left\| F(fish_j) - F(fish_k) \right\|}{2} \quad (5); \quad vis_{scope} = median\left\{ M_{jk} \in M : 1 \le j < k \le N_{fish} \right\} \quad (6)$$

$$features_{ft} = \frac{\sum_{i=1}^{N_{fish}} features_{(i)}}{N_{fish}} \quad (7); \quad features_{ft} \begin{cases} 1 & if \ features_{ft} \ge 0.5 \\ 0 & otherwise \end{cases} \quad (8)$$

$$fish_{i+1} \begin{cases} fish_{y1} & if \ q(F(fish_{y1})) > q(F(fish_{y2})) \\ fish_{y2} & otherwise \end{cases} \quad (9)$$

3. Results and Discussion

The main assumption underlying this study was that changes in the external appearances and surface structure of a food product which is caused by water stress can be detected by visible light imaging techniques. The type of water content measurement performed on cassava chips is the measurement of wet base water content. Measurement of moisture content was done three times for each category of dryness level of B cassava chips for wet (range 1), SK for semi-dry (range 2) and KO for optimal drying (range 3). Based on the measurement of moisture content of the wet base, each grade category of drought level of cassava chips had different water content. The water content in each category was averaged. The average value of the water content of each category of drought-level cassava chips was shown on the graph in Figure 2 and Figure 3.
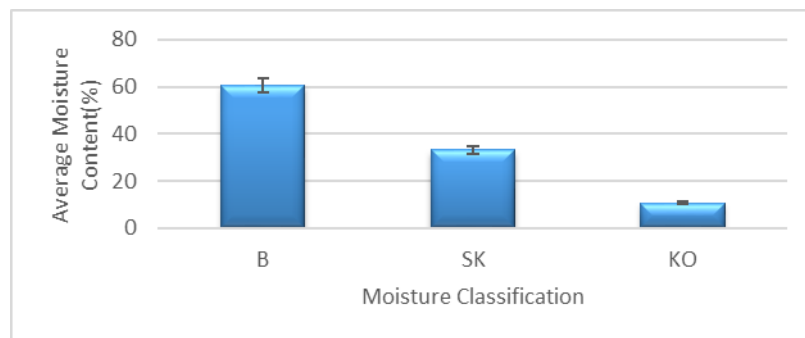
Figure 2. Moisture classification of cassava chips during drying

In Figure 3 typical sample images of cassava chips used in this study were shown where Figure 3a, 3b and 3c were described wet chips, semi-dry chips and dry chips, respectively. Figure 3a to 3c were not distinguishable. Therefore, the application of intelligent approaches to solve this problem. BPNN model performance was tested successfully to describe the relationship between cassava chips water status and image features. It indicated that colour and texture could be good indicators to predict water content in cassava chips during drying. Figure 4 shows that Lab-L has lowest error value compared with other colour parameter that is with MSE value of 0.000247 and absolute relative error (ARE) value of 68.99%. While for the highest error was obtained by Lab-a with MSE value of 0.004197 and ARE value of 91.55%. BPNN results of training and validation on the lowest MSE value of Lab-a was achieved by using hidden layer 20, learning rate 0.4 and momentum 0.1. Figure 5 showed that the MSE value of the best validation result was the energy value with the MSE value of 0.00006 and ARE value of 6.46%, and for the highest value obtained by maximum probability value with MSE of 0.004197 with ARE value of 31.87%. BPNN results of training and validation on the lowest MSE value was energy which was achieved by using hidden layer 20, learning rate 0.4 and momentum 0.1. Figure 6 showed the plot of best normalized fitness values of MOO using FSI. It showed effective in iteration process since the iteration is getting lower through all iterations. Figure 7 showed the training performance of BPNN using FSI and it showed effective in iteration process since the iteration is getting lower through all iterations. By using FSI optimization, the MSE was smaller compare to the method without feature selection optimization. The result of training-set data MSE had the lowest value of 0.0062 with the validation-set data MSE of 0.0135. The R^2 (0.9011) showed acceptable to use the model of ANN to predict the moisture content of cassava chips during drying.
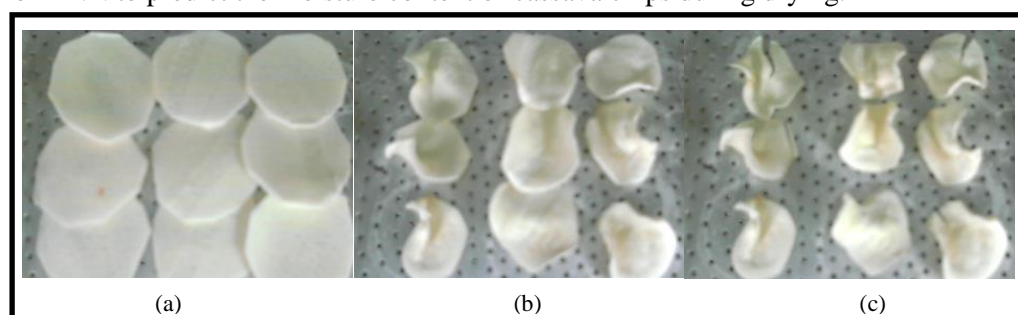

Figure 3. The appearance of cassava chips during drying in different moisture content: (a) wet / range 1; (b) semi-dry / range 2; (c) optimum drying / range 3
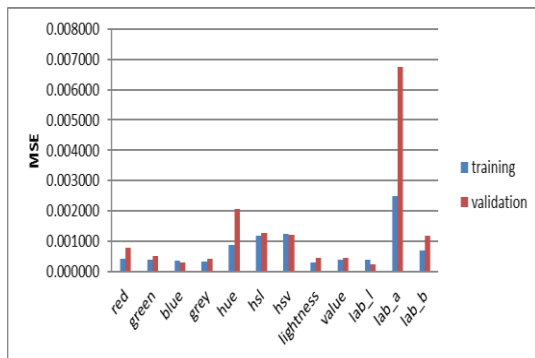
Figure 4. BPNN training and validation results using colour features (*hidden layer* 20, *learning rate* 0.4 and momentum 0.1)
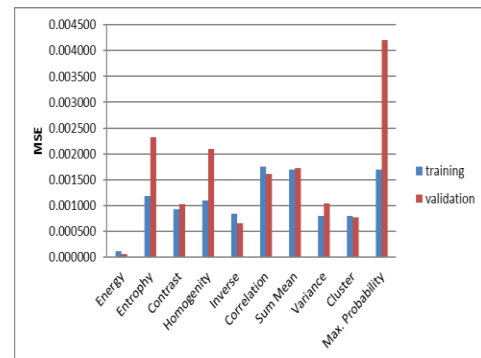

Figure 5. BPNN training and validation results using textural features (*hidden layer* 20, *learning rate* 0.4 and momentum 0.1)
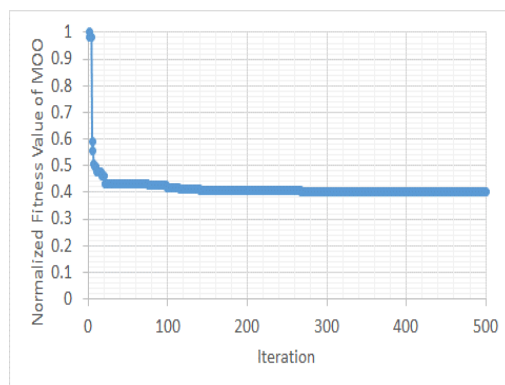

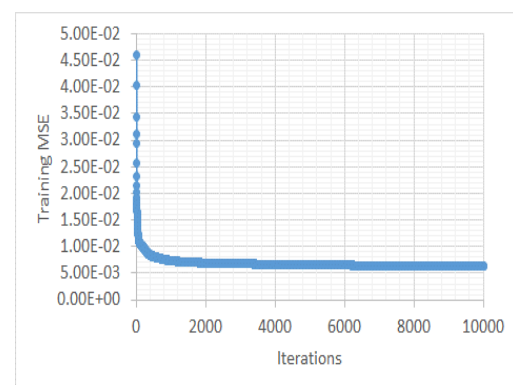**Figure 6.** Plot of best normalized fitness values of MOO using FSI

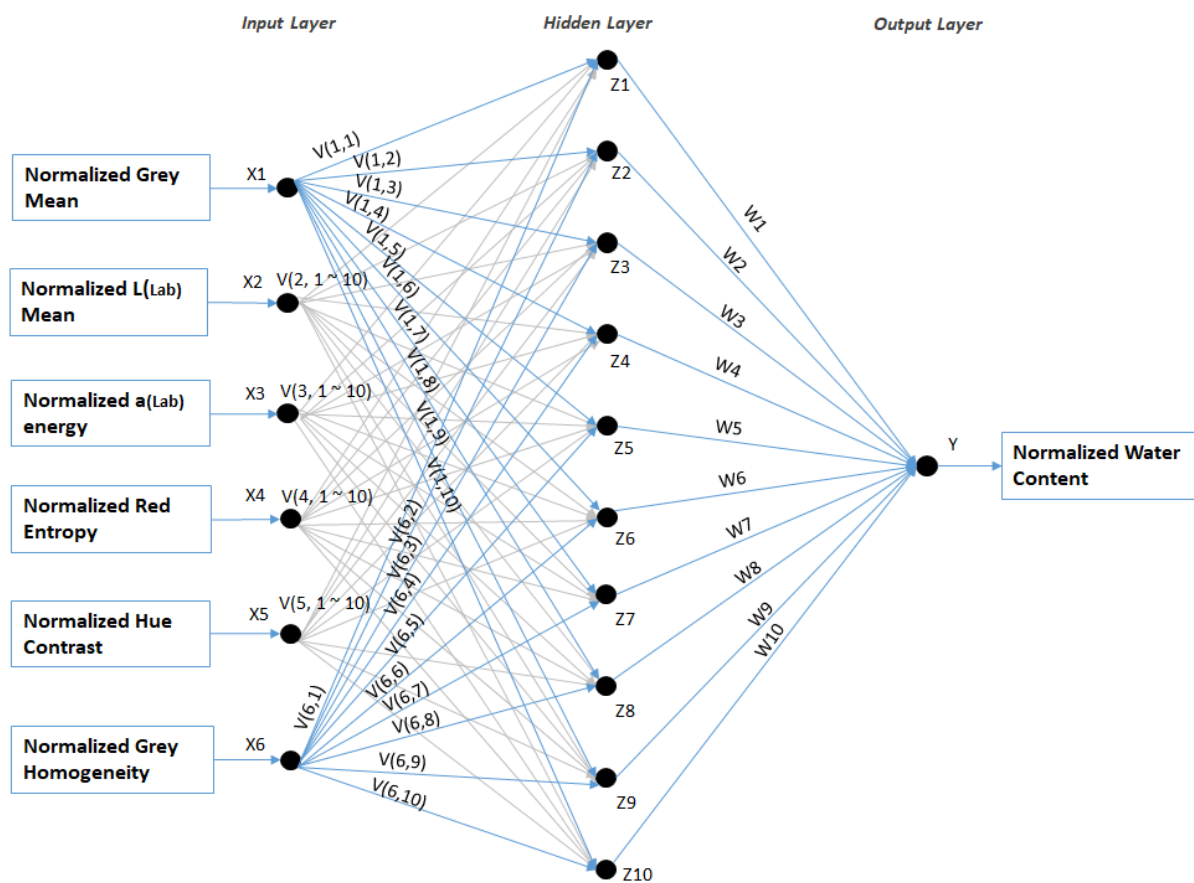**Figure 7.** Training performance of BPNN using FSI

   Table 1 shows the results of the optimum weights from the input layer to the hidden layer which were obtained from the BPNN model. Table 2 shows the results of the optimum weights from the hidden layer to the output layer which were obtained from the BPNN model. Therefore the structure of ANN model was shown in Figure 8.

Table 1. The weights from the input layer to the hidden

V(x,y)		x					
		1	2	3	4	5	6
	1	-1.16497	0.564407	-1.46367	-1.46152	1.920421	-2.56927
	2	-4.91792	-2.62822	-1.0272	2.87E-02	2.5128	-8.30325
	3	-1.44197	0.626267	-2.71323	-0.75411	0.521782	-2.32564
	4	-0.23283	-0.98239	-0.35654	-1.40021	5.38E-02	-0.54782
y	5	2.148937	8.70E-03	2.159154	0.729724	-0.60778	3.108686
	6	-3.97563	7.56E-02	-4.26567	1.088974	-0.39299	-4.30092
	7	0.65281	-1.82747	-5.96E-02	-0.94782	-1.73359	1.039046
	8	9.90E-02	-1.85041	0.745667	-1.49335	-0.60912	0.304743
	9	2.407663	0.409768	1.047853	1.551232	-1.94237	4.3001
	10	0.147574	-0.99473	-0.87917	-1.09507	-0.56111	-0.17694

Table 2. The weights from the hidden to output layer.

W1	-6.84702
W2	-8.07537
W3	-5.61476
W4	-4.62656
W5	2.345198
W6	-6.67257
W7	-5.82548
W8	-4.54159
W9	3.812706
W10	-5.93728

Figure 8. The ANN model

4.   Conclusion

Back-propagation Neural Network (BPNN) has been tested successfully to describe relationship between image features and moisture content in cassava chips during drying. Feature Selection methods using fish swarm intelligent improved the BPNN performance for prediction. Overall, there is a significant difference between methods using feature selection and methods without feature selection.

Acknowledgments

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