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NEURO-NET BASED AUTOMATIC SORTING AND GRADING OF A MUSHROOM(*LENTINUS EDODES L.*)†

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Abstract

Visual features of a mushromm(*Lentinus Edodes L.*) are critical in sorting and grading as most agricultural products are. Because of its complex and various visual features, grading and sorting of mushrooms have been done manually by the human expert. Though actions involved in human grading looks simple, a decision making underneath the simple action comes from the result of the complex neural processing of the visual image. And processing details involved in the visual recognition of the human brain has not been fully investigated yet.

Recently, however, an artificial neural network has drawn a great attention because of its functional capability as a partial substitute of the human brain. Since most agricultural products are not uniquely defined in its physical properties and do not have a well defined job structure, a research of the neuro-net based human like information processing toward the agricultural product and processing are widely open and promissing.

In this paper, neuro-net based grading and sorting system was developed for a mushroom. A computer vision system was utilized for extracting and quantifying the qualitative visual features of sampled mushrooms. The extracted visual features and their corresponding grades were used as input/output pairs for training the neural network and the trained results of the network were presented. The computer vision system used is composed of the IBM PC compatible 386DX, ITEX PFG frame grabber, B/W CCD camera, VGA color graphic monitor, and image output RGB monitor.

Key Word : Neural Net, Back Propagation, Automatic Grading
Mushroom, Computer Vision

Introduction

Quality of a dried mushroom(*Lentinus Edodes L.*) depends mainly on content of moisture and visually characterized external features which can be affected by the growing environment, process of drying, handling, etc. Market price difference corresponding to quality levels is rather high compared to other

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agricultural products. What is worse, the low quality mushroom has a difficulty to be sold.

So far, sorting mushrooms has been roughly done manually and grading has been performed via inspecting randomly selected sample mushrooms by the certified expert. Though grading criterion is specified, its specification is quantitatively rough and includes qualitative descriptions. What is worse, it differs from each country such that Japanese classification is 6 types with 16 grade levels and in Korea 3 types with 12 grade levels. In most case, grading criterion of agricultural products can not be specified precisely in the quantitative sense. In a case of a dried mushroom, the ambiguity of grading criterion increases even more because of the complex and interrelated fuzzy external shape factors.

Generally, human expert is the best in grading individual mushroom but he is usually lack of the consistency and the overall productivity is low because of the fatigue and the illusion. Besides, human decision often varies depending on the emotional state. Therefore, it is required to develop the automatic sorting and grading system which preserves the consistency of grading and improves grading efficiency with the ability of human like robust visual data processing.

Recent advances in the field of artificial neural network have opened the way to a new approach to pattern recognition fields. Since neural network offers many advantages over the previously developed pattern recognition algorithms, many research efforts has been reported related to neuro-net based visual perception and system control.[1,3,4,6] In a word, neural net is known to be good(poor) at solving problems which human is good(poor) at. High computing rate, a great degree of fault tolerance provided by massively parallel information processing, and capability of learning and generalization are the most notable advantages.

This paper aims to develop the neuro-net based efficient mushroom grading algorithm utilizing quantitative features obtained from the computer image processing.

Visual Feature Oriented Neuro-Net Grading

The computer vision system used is composed of the IBM PC 386DX, ITEX PFG frame grabber, B/W CCD camera, VGA graphic monitor, and image output RGB monitor. The functional block diagram of training grading aspect of the human expert and process of grading via trained network is shown in Fig. 1.

Human often percepts the visual image with ease from the charateristics of the extracted features rather than from the raw image. Network was also trained by inputing extracted quantitative features obtained from computer image processing instead of raw image.

Japanese grading criterion(6 types with 16 grades) was used and sample mushrooms were randomly selected and graded by the expert. These grading results were used for training network.

1. Generalized error back propagation(BP) network

In this section, the structure and learning function of the well known BP network are briefly explained. The error back propagation network, called as

BP network, is a muti-layered network generalizing the delta rule for the connection weight adjustment. Delta rule is a kind of network training algorithm which was developed for networks with linear units whose activation function is defined as linear. The structure of BP network is same as multi-layered perceptron but the connection weigts among nodes are adjusted by back propagateing the output error. And network training is done in the supervised way.

BP network consists of three or more layers. The bottom layer of the network is called input layer, the most upper layer is called the output layer and intermediate layers are called hidden layer. Each layer has a number of units, called neurons. Each unit of the input layer may represent an element of a pattern vector given from the outside or independently represent a certain sensory input. Magnitudes of all input are usually normalized to have similar ranges. Each unit is connected to all units in the layer above. Given problem, after specifying structures of input and output layers, the optimum number of intermediate layers and units in each intermediate layer are usually decided as an ad hoc basis.

Each unit of BP network has a nondecreasing and differentiable semi-linear activation function. A sigmoid type logistic function is frequently used for the activation function. Since the logistic function asymptotically reaches 0 and 1, target output is often set as values near 0 and 1. Except for the input layer units, the net input to each unit is the sum of the weighted outputs of the units in the prior layer. Net input to a unit j from the units in the previous layer is defined as follows.

$$net_j = \sum w_{ji}\, o_i$$

where, w_{ji} is the connection weights from unit i of the previous layer to unit j and o_i is the output of the unit i. Initially every connection weight is assigned with small random value to avoid a certain training pathology caused by the weight symmetry[5].

The output of unit j is defined as

$$o_j = f(net_j)$$

where, f is an activation function. A sigmoid type logistic activation function is defined as

$$o_j = \frac{1}{1 + \exp[-(net_j + \theta_j)]}$$

where, θ_j is a bias of neuron j and bias is similar to threshold. Bias offsets the origin of the logistic activation function and has an effect of rapid convergence of training. Since input units do not have bias, practically dummy unit whose output is one is assigned at each layer.

Training of the network is done iteratively. Terminating conditions such as maximum number of iterations or tolerance of the total trained error are required. Error at each output unit computed from comparing with desired target value is propagated backward through the network and is used to adjust the connection weight. For the given sets of input patterns or images, overall measure of the trained error is defined as

$$E = \sum_p E_p = \frac{1}{2} \sum_p \sum_j (t_{pj} - o_{pj})^2$$

Where, p denotes a single input pattern.

The idea of the error back propagation learning rule is based on the gradient descent approach which adjusts weights proportional to the negative of the derivative of the ovarall trained error with respect to each weight. Details on implementing the generalized delta rule to the gradient descent approach refer to McClelland and Rumelhart(1987).

The connection weight is adjusted such that

$$[w_{ji}]_{NEW} = w_{ji} + \Delta w_{ji}$$

$$\Delta w_{ji} = \zeta\ \delta_j\ o_i$$

Where, δ_j is computed for the output and hidden layer. Details on computing δ_j also refer to McClelland and Rumelhart(1987). And ζ denotes a learning rate. Large learning rate causes large change of weight resulting into oscillation.

The way to increase learning rate without oscillation has been reported as follows.

$$\Delta w_{ji}(t+1) = \zeta\ \delta_j\ o_i + \alpha\ \Delta w_{ji}(t)$$

Where, α denotes the momentum rate which determines the effect of the past weight changes on the current direction of movement in weight space. Great deal of research efforts is still on going to improve the performance of BP network related to the topics such as training efficiency, optimum structure, network paralysis, local minima, post processing of output, etc.

BP training is done by two stages forward and backward. At the forward stage, sets of input and output pattern pairs are presented and compute the network output. Then at the backward pass error signals obtained from the final layer are back propagated. Details on the process refer to McClelland and Rumelhart(1987) or Pao(1989).

2. Classification of simple geometric primitives

First, training performance of BP network was simulated using the sampled simple polygons and circle. Visual features such as complexity, roundness, ratio of maximum to average distance from centrod to boundary, and ratio of average to minimum distance from centrod to boundary were quantified via computer vision system. Selected features are independent of scale, location, and orientation of the object image. And each input feature was rescaled to have similar ranges of values.

The structure of the network is formed as 3 input units, 5 hidden units, and 3 output units. Table 1 shows 7 sample primitives used for network training, corresponding quantitative values of visual features, desired output values for classification, and output of the trained network for each sample image. In programming, target values of 0 and 1 were converted to 0.05 and 0.95 considering characteristics of a logistic activation function. Learning and momentum rates were assigned as 0.7 and 0.9 respectively. Normalized system error which is the squared sum of target and output difference over total numer of input samples was set 0.001. As shown in table 1, network was trained well enough to classify correctly given samples.

Using the trained network, classification of untrained and degraded primitives were tested. Table 2 shows the classification results obtained. Because of the generalization property of the network, network generated quite reasonable and robust output to fuzzy and degraded inputs.

3. Mushroom grading

Since all the sample mushrooms for each grade were not available, 21 sampled mushrooms(3 per each grade) were graded first by the expert as 4 types with 7 grade levels. Seven visual features were selected and quantified via computer vision system and used for the network training. Selected visual fetures were shape, color, state of crack, texture of skin, average radius, thickness, membrane state.

Shape, size, and color(degree of brown color) of a mushroom cap were quantified as roundness, average radius, and overall average gray value respectively. State of crack on the cap skin was quantified as summed deviation between average gray value of each quadrant and overall intensity. Texture of skin was evaluated using wighted sum of overall gray value and state of crack. Thickness and membrane state were quantified as the amount of rolled skin and average gray value of membrane respectively. Values of input features were rescaled to have values in the range 0 to around 1. Details on quantifying visual features refer to Han(1991).

As shown in fig. 2, network structure was formed with 7 units for input, 8 units for hidden, and 3 units for output layer. 3 units in the output layer can classify all the input patterns into 8 categories. Learning and momentum rates were assigned as 0.7 and 0.9 respectively. Maximum total error, was set as 0.05 and maximum number of iteration was set 3000. As shown in table 4, network was trained well enough to classify sample mushrooms correctly.

Finally, the network has been trained using 50 sample mushroom data for full grading of 6 types with 16 levels according to the Japanese grading criterion. Since samples per every grade level were not available, visual data for the missing samples were made artificially by carefully inspecting real scaled pictures and descriptions of a mushroom(*Lentinus Edodes L.*) presented in the Japanese grading catalog.

Aspects of training are shown in table 5. Since computing load was too much to train visual features of all 50 samples at one time, 50 samples were separated into 5 sets. First, a set having 10 samples was trained and then consequtively next set was added and trained using the pretrained weight data. This training scheme reduced a great deal of training time. Resulting iteration number for each training stage is shown in table 6. Table 7 shows values of input visual features of 50 sample mushrooms used for training, target output values. Training was done successfully and table 8 shows the trained results. Here, output value 0 and 1 of the trained network were caused by the rounding.

Experimentally, 50 samples were randomly chosen and grading test was done. Grading results of 4 samples were suspicious and others were correctly graded.

Conclusion

In this paper, we proposed the relatively robust mushroom grading system which can mimic human's grading capability while keeping consistency and improving productivity. Using multilayer error back propagation network, grading of a dried mushroom(*Lentinus Edodes L.*) was successfully done via inputing quantitative visual features obtained from computer vision system.

Grading capability of the proposed scheme was perfect for samples used for training.

Once network is trained, grading is done in a sense of open loop. To improve the grading accuracy of the network, it is suggested that enough samples per each grade level be trained. Because of the property of generalization of the network there will be no problem to grade unknown mushrooms once the network is fully trained with enough samples. Collecting misgraded samples and retraining the previously trained network with previous sampls and collected ones will increase grading performance of the network and reduce the training period.

Further research on selecting input features of the network and direct training of raw image input is suggested to realize the real time implementation of the neuro-net based mushroom grading system.

Reference

1. Widrow, B. 1987. DARPA Neural Network Study, AFCEA Int. Press
2. Han, J.H. 1991. Extraction and Recognition of The Patterns of Lentinus Edodes Using Computer Vision, MS Thesis, SungKyunKwan Univ. Dept. of Agr. Mach. Eng.
3. Miller III, W.T., R.S. Sutton and P.J. Werbos. 1990. Neural Networks for Control, MIT Press.
4. Richard P.Lippmann. 1987. An introduction to computing with neural nets, IEEE ASSP Magazing, pp 4-22.
5. Rumelhart, D.E., G.E. Hinton and R.J. Williams. 1988. Learning internal representations by error propagation, Parallel Distributed Processing; Explorations in the Microstructure of Cognition, Vol.1, Editor; David E. Rumelhart, James L.McClelland, and PDP Group MIT Press. pp 318-362.
6. Pao, Y.H. 1989. Adaptive Pattern Recognition and Neural Networks, Addison Wesley Inc., pp 113-140.

Table 1. Training classification of simple geometric primitives
(R:Roundness, CR:Complex Ratio, DO:Desired Output, M/A:Max. to Avg. Ratio, A/M:Avg. to Min. Ratio, TNO:Trained Network Output)

Feature Sample	R	CR	M/A	A/M	DO	TNO
	1.477	0.834	0.875	0.750	1 1 1	0.952 0.947 1.000
	0.893	1.380	1.308	1.207	1 1 0	0.952 0.940 0.002
	1.413	0.871	0.908	0.764	1 0 1	0.947 0.055 1.000
	0.877	1.405	1.383	1.371	1 0 0	0.949 0.062 0.053
	1.287	0.957	1.033	0.821	0 1 1	0.052 0.951 0.949
	1.103	1.117	1.183	1.071	0 1 0	0.050 0.996 0.052
	1.027	1.200	1.133	1.464	0 0 1	0.049 0.018 0.948

Table 2. Trained network out for unknown degraded samples
(R:Roundness, CR:Complex Ratio, DO:Desired Output, M/A:Max. to Avg. Ratio, A/M:Avg. to Min. Ratio, TNO:Trained Network Output)

Feature Sample	R	CR	M/A	A/M	TNO
	1.460	0.844	0.850	0.771	0.952 0.886 1.000
	1.012	1.218	1.300	1.057	0.789 0.997 0.001
	1.377	0.895	0.925	0.843	0.917 0.019 1.000
	0.968	1.272	1.367	1.400	0.855 0.032 0.194
	1.278	0.964	1.017	0.893	0.021 0.984 0.853
	1.162	1.061	1.267	1.007	0.043 0.998 0.038
	1.018	1.210	1.275	1.557	0.330 0.015 0.756

Table 3. Input features of 7 graded 21 sample mushrooms(3 per grade level) and target value of each level
(L:Large Size M:Medium Size S:Small Size
HQ:High Quality LQ:Low Quality)

Feature / Sample	Shape	Color	Crack state	Skin state	Size	Thick-ness	Memb. state	Desired Value
HwaGo (L)	0.833	0.70	0.50	0.73	0.24	1.05	0.81	1 1 1
	0.840	0.72	0.55	0.75	0.25	1.15	0.91	
	0.843	0.81	0.53	0.81	0.25	1.20	0.88	
HwaGo (S)	0.737	0.72	0.50	0.73	0.18	0.70	0.85	1 1 0
	0.807	0.70	0.52	0.74	0.18	0.71	0.87	
	0.827	0.80	0.51	0.79	0.18	0.75	0.87	
DongGo (HQ.L)	0.807	0.53	0.25	0.65	0.22	1.15	0.88	1 0 1
	0.800	0.54	0.27	0.65	0.23	1.08	0.89	
	0.801	0.46	0.33	0.27	0.23	0.34	0.89	
DongGo (HQ.M)	0.807	0.55	0.28	0.66	0.18	0.90	0.87	1 0 0
	0.811	0.57	0.31	0.67	0.18	0.88	0.88	
	0.800	0.48	0.25	0.25	0.18	0.27	0.85	
HyangGo (HQ)	0.830	0.66	0.40	0.60	0.29	1.21	0.85	0 1 1
	0.830	0.64	0.39	0.65	0.34	1.30	0.85	
	0.829	0.67	0.41	0.63	0.32	1.33	0.87	
HyangGo (LQ)	0.790	0.55	0.28	0.35	0.30	0.42	0.86	0 1 0
	0.820	0.53	0.30	0.35	0.31	0.40	0.86	
	0.830	0.57	0.32	0.38	0.31	0.40	0.85	
Bad	0.560	0.29	0.58	0.19	0.11	0.00	0.60	0 0 1
	0.500	0.35	0.61	0.14	0.21	0.01	0.51	
	0.525	0.25	0.72	0.18	0.41	0.02	0.63	

Table 4. Trained results of 21 sample mushrooms
(L:Large Size M:Medium Size S:Small Size
HQ:High Quality LQ:Low Quality)

Output / Sample	Output 1	Output 2	Output 3	Target Value
HwaGo (L)	0.9946	0.8795	0.6290	1 1 1
	0.9900	0.8900	0.8536	
	0.9820	0.9092	0.9371	
HwaGo (S)	0.9676	0.9402	0.1409	1 1 0
	0.9668	0.9317	0.1313	
	0.9797	0.9397	0.1671	
DongGo (HQ.L)	0.9996	0.0002	0.9945	1 0 1
	0.9999	0.0002	0.7518	
	0.9111	0.0148	0.0063	
DongGo (HQ.M)	0.9999	0.0001	0.0345	1 0 0
	0.9999	0.0003	0.0333	
	0.9626	0.0034	0.0046	
HyangGo (HQ)	0.2969	0.9484	0.9999	0 1 1
	0.0951	0.9628	0.9999	
	0.0821	0.9608	0.9999	
HyangGo (LQ)	0.1713	0.9235	0.0183	0 1 0
	0.1596	0.9280	0.0190	
	0.0568	0.9880	0.0273	
Bad	0.0940	0.0000	0.9754	0 0 1
	0.0018	0.0129	0.9946	
	0.0014	0.0096	0.9964	

Table 5. Learning aspects of BP Network

Number of Input feature	7
Number of Output Units	4
Total No. of Input Samples	50
Momentum Rate	0.9
Learning Rate	0.7
Maximum Total Error	0.05
Individual Error	0.005
Maximum No. of Iteration	3000
Number of hidden Layer	1
No. of units for Hidden Layer	8

Table 6. Iteration number and normalized sytem error of each training

Sample No.	Iteration No.	Normalized System Error
10	717	0.04783
20	934	0.04737
30	89	0.04768
40	374	0.04876
50	618	0.04677

Table 7. Input features of 16 graded 50 sample mushroom and target value of each grading (16 graded 50sample mushrooms)
(L:Large Size M:Medium Size S:Small Size
HQ:High Quality LQ:Low Quality)

Feature / Samples	Shape	Color	Crack	Skin State	Size	Thick-ness	Memb. State	Output Target Value
HwaGo (L)	0.83	0.70	0.50	0.73	0.24	1.05	0.81	
	0.84	0.72	0.55	0.75	0.25	1.15	0.91	1 1 1 1
	0.84	0.81	0.53	0.81	0.25	1.20	0.88	
HwaGo (S)	0.74	0.72	0.50	0.73	0.18	0.70	0.85	
	0.81	0.70	0.52	0.74	0.18	0.71	0.87	1 1 1 0
	0.83	0.80	0.51	0.79	0.18	0.75	0.87	
DongGo (HQ.L)	0.81	0.53	0.25	0.65	0.22	1.15	0.88	
	0.80	0.52	0.25	0.65	0.22	1.05	0.86	1 1 0 1
	0.80	0.54	0.27	0.65	0.23	1.08	0.89	
DongGo (HQ.M)	0.81	0.55	0.28	0.66	0.18	0.90	0.87	
	0.81	0.55	0.30	0.68	0.18	0.89	0.87	1 1 0 0
	0.81	0.57	0.31	0.67	0.18	0.88	0.88	
DongGo (LQ.L)	0.73	0.44	0.26	0.26	0.22	0.35	0.88	
	0.80	0.44	0.32	0.27	0.23	0.36	0.88	1 0 1 1
	0.80	0.46	0.33	0.27	0.23	0.34	0.89	
DongGo (LQ.M)	0.76	0.45	0.26	0.25	0.18	0.29	0.87	
	0.80	0.48	0.25	0.25	0.18	0.29	0.85	1 0 1 0
	0.80	0.46	0.28	0.24	0.18	0.27	0.84	
DongGo (S)	0.74	0.55	0.32	0.35	0.09	0.23	0.85	
	0.79	0.45	0.33	0.35	0.09	0.23	0.87	1 0 0 1
	0.79	0.47	0.34	0.29	0.09	0.21	0.83	
HyangGo (HQ)	0.83	0.66	0.40	0.60	0.29	1.21	0.85	
	0.83	0.64	0.39	0.65	0.34	1.30	0.85	1 0 0 0
	0.83	0.67	0.41	0.63	0.32	1.33	0.87	
HyangGo (LQ)	0.79	0.55	0.28	0.35	0.30	0.42	0.86	
	0.82	0.53	0.30	0.35	0.31	0.40	0.86	0 1 1 1
	0.83	0.57	0.32	0.38	0.31	0.40	0.85	
HyangSin (HQ.L)	0.70	0.44	0.25	0.25	0.32	0.20	0.78	
	0.74	0.46	0.25	0.26	0.33	0.21	0.79	0 1 1 0
	0.74	0.46	0.25	0.26	0.33	0.21	0.81	
HyangSin (HQ.M)	0.69	0.47	0.29	0.28	0.25	0.19	0.77	
	0.75	0.48	0.29	0.29	0.26	0.19	0.78	0 1 0 1
	0.75	0.46	0.29	0.29	0.25	0.18	0.78	
HyangSin (HQ.S)	0.70	0.48	0.25	0.25	0.15	0.15	0.75	
	0.72	0.49	0.26	0.25	0.15	0.15	0.75	0 1 0 0
	0.72	0.47	0.26	0.24	0.15	0.15	0.76	
HyangSin (LQ.L)	0.62	0.40	0.35	0.24	0.32	0.11	0.72	
	0.62	0.43	0.35	0.24	0.33	0.12	0.73	0 0 1 1
	0.62	0.43	0.37	0.23	0.33	0.10	0.74	
HyangSin (LQ.M)	0.59	0.39	0.36	0.26	0.25	0.09	0.73	
	0.60	0.38	0.37	0.26	0.26	0.09	0.74	0 0 1 0
	0.60	0.37	0.38	0.24	0.25	0.08	0.74	
HyangSin (LQ.S)	0.61	0.40	0.35	0.25	0.15	0.08	0.70	
	0.60	0.41	0.34	0.26	0.16	0.07	0.70	0 0 0 1
	0.60	0.42	0.37	0.23	0.15	0.07	0.71	
Bad	0.40	0.30	0.60	0.13	0.25	0.01	0.65	
	0.46	0.25	0.50	0.17	0.31	0.02	0.55	
	0.56	0.29	0.58	0.19	0.11	0.00	0.60	0 0 0 0
	0.50	0.35	0.61	0.14	0.21	0.01	0.51	
	0.53	0.25	0.72	0.18	0.41	0.02	0.63	

Table 8. Trained Results of 50 sample mushrooms
(L:Large Size M:Medium Size S:Small Size
HQ:High Quality LQ:Low Quality)

output sample	Output 1	Output 2	Output 3	Output 4	Target
HwaGo (L)	0.99774 0.99987 0.99788	0.99888 0.90017 0.99921	0.99797 0.97230 0.99738	0.99956 0.99995 0.98899	1 1 1 1
HwaGo (S)	0.99999 0.99999 0.99999	0.99626 0.99089 0.99914	0.98601 0.97907 0.99493	0.00008 0.00010 0.00025	1 1 1 0
DongGo (HQ.L)	1.00000 1.00000 1.00000	0.99878 0.99997 0.99891	0.00000 0.00000 0.00000	0.99801 0.94827 0.98817	1 1 0 1
DongGo (HQ.M)	1.00000 1.00000 1.00000	0.99999 0.99999 0.99994	0.00003 0.00012 0.00020	0.10218 0.01517 0.01163	1 1 0 0
DongGo (LQ.L)	0.99922 0.99927 0.99943	0.00032 0.00033 0.00023	0.99998 0.99998 0.99997	0.99839 0.99947 0.99871	1 0 1 1
DongGo (LQ.M)	0.99998 0.99136 0.99963	0.00002 0.03110 0.00034	0.99910 0.99950 0.99616	0.02029 0.00003 0.00070	1 0 1 0
DongGo (S)	0.99036 0.99975 0.99683	0.00257 0.00002 0.00006	0.00214 0.00074 0.00006	0.99999 1.00000 0.99999	1 0 0 1
HyangGo (HQ)	1.00000 1.00000 1.00000	0.06176 0.09342 0.05533	0.00003 0.00003 0.00003	0.02378 0.02272 0.02434	1 0 0 0
HyangGo (LQ)	0.04113 0.04268 0.03442	0.99535 0.99463 0.99677	1.00000 1.00000 1.00000	0.99714 0.99735 0.99657	0 1 1 1
HyangSin (HQ.L)	0.00000 0.00000 0.00000	0.99998 0.99999 0.99999	0.99999 0.99998 0.99999	0.00860 0.00114 0.00076	0 1 1 0
HyangSin (HQ.M)	0.00002 0.00000 0.00001	0.99981 0.99998 0.99992	0.00789 0.04846 0.01205	0.98409 0.99329 0.96460	0 1 0 1
HyangSin (HQ.S)	0.00264 0.00265 0.00481	0.99295 0.99233 0.97907	0.00009 0.00008 0.00006	0.03962 0.04442 0.07329	0 1 0 0
HyangSin (LQ.L)	0.00000 0.00000 0.00000	0.00003 0.00028 0.00002	0.99999 0.99999 0.99999	0.95502 0.97879 0.98603	0 0 1 1
HyangSin (LQ.M)	0.00000 0.00000 0.00000	0.00000 0.00000 0.00000	0.96223 0.96916 0.94548	0.01086 0.01943 0.02793	0 0 1 0
HyangSin (LQ.S)	0.11507 0.02629 0.07437	0.00766 0.03593 0.00105	0.00000 0.00001 0.00001	0.90090 0.64039 0.90608	0 0 0 1
Bad	0.00001 0.00000 0.00001 0.00001 0.00000	0.00000 0.00000 0.00000 0.00000 0.00000	0.02594 0.09049 0.04726 0.03426 0.06287	0.00337 0.00751 0.00507 0.00318 0.08001	0 0 0 0

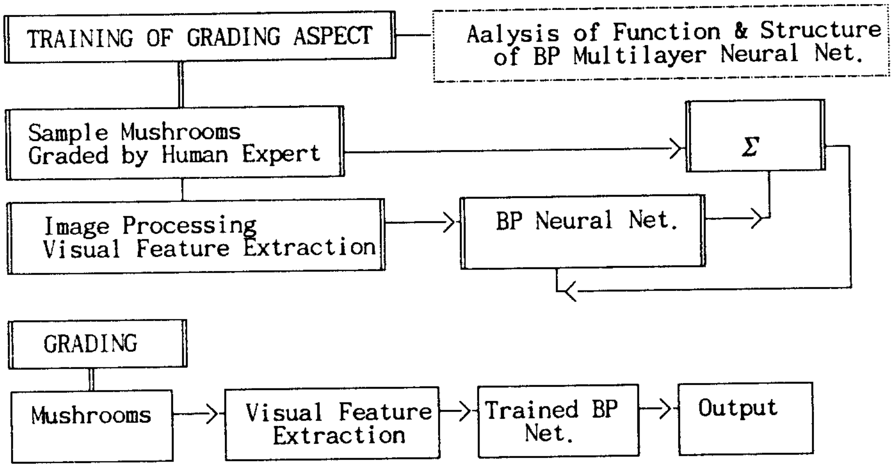

Fig 1. Block diagram of Image processing and Grading by BP Nework.

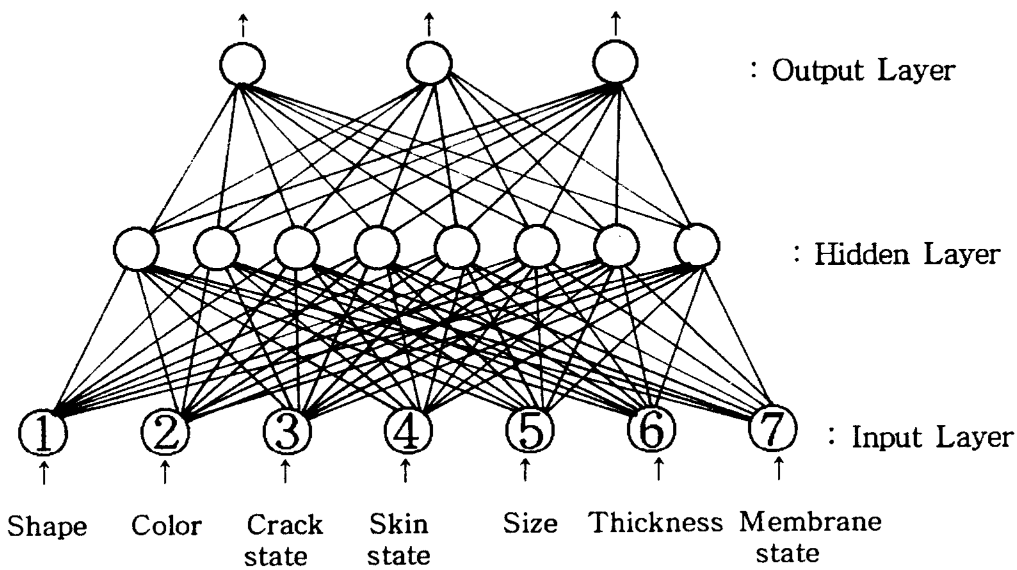

Fig. 2 Structure of the generalized error back propagation network and visual input features.