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Research Article

Feed Forward Neural Network for Solid Waste Image Classification

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Abstract: This study deals with the Feed Forward Neutral Network (FFNN) model to classify the level content of waste based on teaching and learning concept. An FFNN with twenty images is used for testing the input samples through the neural network learning to compute the sum squared error to ensure the performance of the model. After several training the neural network was able to learn and match the target. Thirty images for each class are used as a fullest of inputs samples for classifying. Result from the neural network and the rules decision are used to build the Receiver Operating Characteristic (ROC) graph. Decision graph show the performance of the system based on Area Under Curve (AUC) for the solid waste system is classified as WS-Class equal to 0.9875 and as WS-grade equal to 0.8293. The system has been successfully designated with the motivation of waste been monitoring system, to escalate the results that can applied to wide variety of local municipal authorities system.

Keywords: Artificial neural network, hough transforms, image classification, solid waste

INTRODUCTION

Digital image processing technology has been widely used in many scopes such as biology, food engineering, environment and medical care and so on. Image processing of very close range video images or digital photographs are currently used for verification of level volume of waste inside the bin (Arebey *et al*., 2012). Image processing will be applied for waste level verification based on several researchers working in various applications in image processing (Shylaja *et al*., 2011; Hannan *et al*., 2011a, b; Arebey *et al*., 2011; Hamarneh *et al*., 1999; Jiazhi *et al*., 2007). Image analysis is a part in image processing stage, by using the specific algorithm to process digital image presented a method to analyze the effect of drying on shrinkage, color and image texture which were classified into classes depending on external image feature (Jiazhi *et al*., 2007).

The implementation of machine vision in image analysis can be designed to solve a variety of industrial tasks such as waste monitoring. Many kind of machine vision technology have been employed including spectral devices and digital camera (Hannan *et al*., 2010; Jiazhi *et al*., 2007). The challenges are countered in a typical industrial environment to develop the robust machine vision system for development of an appropriate illumination set-up, optimal interfacing between the sensing and optical system (Artzai *et al*., 2010). The system development has been subjected to a thorough evaluation and to replace the manual procedure.

Waste classification verification technique is been used for verify the level of waste (Arebey *et al*., 2011). Matching algorithm has been investigated by using image based verification on a gray-scaled image without pre-processing. This correlation coefficient approach is capable of finding the correspondences between the input image and the stored enrolled template with the high matching rate. Artificial Intelligence (AI) techniques such as Neural Network are applied for pattern verification. AI techniques are used to determine where to weld these sorts of part for automated welding system (David *et al*., 2010). The image capture methods are being combined with a decision-making system that uses multiple parallel AI technique. Aouache (2006) presents an effort to develop real-time weed sensing technologies using machine vision.

In this study, Feed Forward Neutral Network (FFNN) model is to be used for solid waste bin level classification and grading. An advanced image processing technique was to use for solid waste feature extraction using Hough transform and applied into FFNN model for waste classification and verification. A fixed number of image samples were trained using neural network back propagation error steps. An area under ROC curve was used to measure the discriminating ability of classification model.

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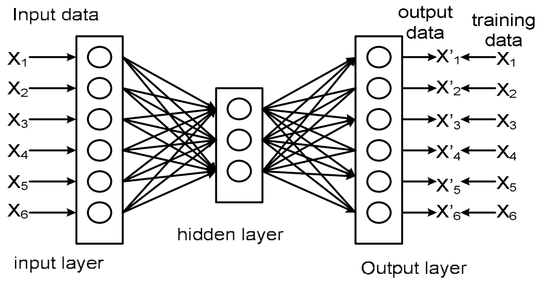

Fig. 1: Multilayer feed forward neural networks

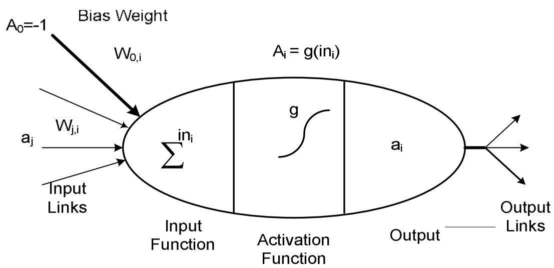

Fig. 2: A simple mathematical models for a neuron

FEED FORWARD NEURAL NETWORK (FFNN)

Artificial Neural Network (ANN) is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use (Negnevitsky, 2005; Richard, 2006). The ANN based model have been explored for use in monitoring the level of waste inside the bin. The development of an Artificial Neural Network (ANN) models based on waste level verification system that can be classify the level content of waste inside the bin. The Feed Forward Neural Network (FFNN) known as Multilayer Perceptions (MLP) used here is a one type of Back propagation neural network. FFNN was the first and arguably simplest type of ANN devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden not (if any) and to the output nodes as shown in Fig. 1.

The number of input layer, hidden layers and output layers are adjusted to fit the data point to the line. A three-layer feed-forward back propagation ANN was built by using the MATLAB® neural network toolbox. Multilayer networks trained by the back propagation algorithm are capable of learning nonlinear decision surfaces and this make efficient and compact classifier. During the training phase the training data in the accumulator array is fed into the input layer. The data is propagated to the hidden layer and then to the output layer. This is the forward pass of the back propagation algorithm. Each node in the hidden layer gets input from all the nodes from input layer which are multiplexed with appropriate weights and summed.

The output of the hidden note is the nonlinear transformation of the resulting sum. Similar procedure is carried out in the output layer. The output values are compared with target values and the error between two is propagated back towards the hidden layer. This is the backward pass of the back propagation algorithm. The procedure is repeated to get the desired accuracy. During the testing phase the test vector is fed into the input layer. The output of FFNN is compared with training phase output to match the correct one. This can serve as a need to verify the waste bin level.

FFNN model: An artificial neural network or as a neural network is a mathematical model for information processing based on a connectionist approach to neural computation. Figure 2 shows a simple mathematical model of neuron devised by Russell and Norvig (2003) in which the neural networks are composed of nodes or units connected by directed link. A link from unit j to unit i serve to propagate the activation α_j from j to i. Each link has a numeric weight $W_{j,i}$ associated with it, which determines the strength and sign of the connection. Each unit i first computes a weighted sum of its inputs:

$$in_i = \sum_{j=0}^{n} W_{j,ia_j} \quad (1)$$

Applies an activation function g to this sum to derive the output:

$$a_i = (in_{i)} = g\left(\sum_{j=0}^{n} W_{j,ia_j}\right) \quad (2)$$

We notice a bias weight $W_{o,i}$ connected was included to affixed input $a_o = -1$. The unit's output activation is $a_i = \sum_{j=0}^{n} W_{j,ia_j}$), where a_j is the output activation of and unit j and $W_{j,i}$ is the weight on the link from unit j to this unit.

To meet two desiderata, the activation function g was designed, the unit to be 'active' (near +1) when the 'right' input are given and in 'active' (near o) when the 'wrong' inputs are given. Second, the activation needs to be nonlinear; otherwise the entire neural network collapses. Two choice of g are shown in Fig. 3 as the threshold function and the sigmoid function. The sigmoid curve is used as a transfer function because it has the effect of 'squashing' the inputs into the range (-1, 1). It is simple derivative function for back propagating errors through a feed forward neural network. This is the function used for the perception algorithm written in MATLAB to create neuron that makes a classification decision. There are two modes of learning process, supervised learning and unsupervised learning. The Feed Forward network usually use supervised learning process, the predicted output is compared to the actual output for that case.

Too more closely into the assertion that a feed forward networks represents a function of its input. Refer to the Fig. 4, the simple network with two input

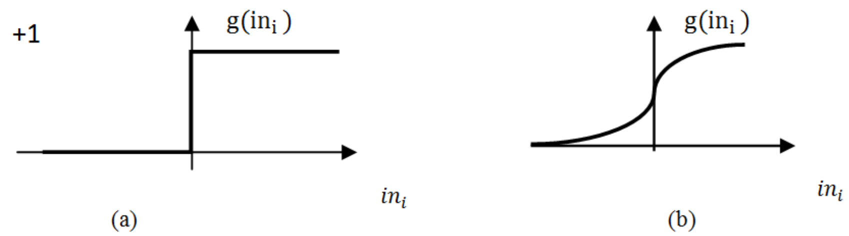

Fig. 3: (a) the threshold activation function, which output 1 when the input is positive and 0 otherwise (b) the sigmoid function 1/ (1+e^{-x})

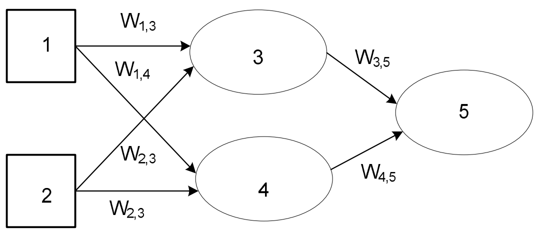

Fig. 4: Neural networks with two inputs, one hidden layer of two units and one output

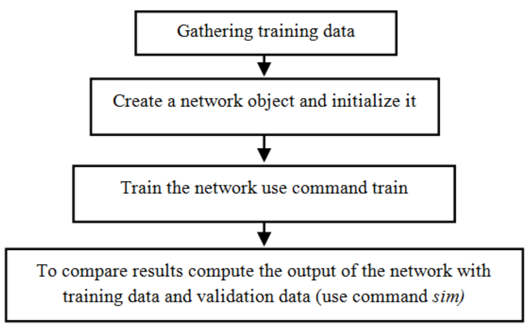

Fig. 5: Back propagation neural network block diagram

units, two hidden units and output units are explained as follows:

$$a_5 = g(W_{3,5a_3} + W_{3,5a_4}) = g(W_{3,5g} (W_{1,3a_1} + W_{2,3a_2}) + W_{4,5g}(W_{1,4a_1} + W_{2,4a_2}) \quad (3)$$

The expression of the output of a_5 is a function of network's inputs.

FFNN implementation: Various types of ANNs have been create successfully in various applications using MATLAB implementation of FFNN from the Neural Network Toolbox Version 4.0.2 of MATLAB V6.5 (R13) and to build the ANN image recognition models. Figure 5 shows the steps when implementing back propagation neural network. The command MATLAB *new ff* defines the network. It is type of architecture, size and type of training algorithm to be used. *New ff* indicates the type of neural network used FFNN. MATLAB uses batch training for back propagation, which means that the weights and biases are updated after the whole training set has been applied to the net. At the same time define the structure of the network. There are several training algorithms that can be used, depending on the application, but MATLAB uses trainlm (Levenberg-Marquardt algorithm) by default if we do not specify, which is the fastest of the training algorithms (Aouache, 2006). Command *sim* are used to show the simulation result where to compute the result with the output of network training data and validation data.

FFNN Hough transform model: In this project, mode of training process was implemented for reason to increase the rate verification of our classification system. Typical feed forward neural networks are designated to perform the training process. During the training session, the sum of the squared errors is a useful indicator of the network's performance. The Maximum Sum Squared Error (MSE) was setting to 1e-3 with 100000 epoch's time number to precede the training process. A three-layer back propagation neural network (10, 5, 2) was built by using the MATLAB neural network toolbox. *New ff* defines feed-forward network architecture with the (10, 5, 2) defines the range of the input and initializes the network parameters. The structure of network show the 10 is the number of the nodes in the first hidden layer, 5 is the number of tansig function, 2 is the number of nodes in the output layer. To achieve performance goal met, the transfer function used for all and the lines was a tangent sigmoid transfer function 'tansig' and to train the neural network 'traingdm' were selected. Twenty images from each class of waste bin level as used the full set of inputs samples for training.

As the neural networks learn, the training curve, present the full set of inputs samples through the neural network to compute the sum squared error function we will use in the back propagation of errors step. The convergence curve show a chance to improve the network parameters by increasing the number of iterations (epochs). Each such pass is called epoch we can see graphically, at 28257 epochs we reach to goal of met, MSE 0.000999994/ 0.001, Gradient 0.00239639/1e-010. For development of the Waste System classifier, the ANN was trained based on

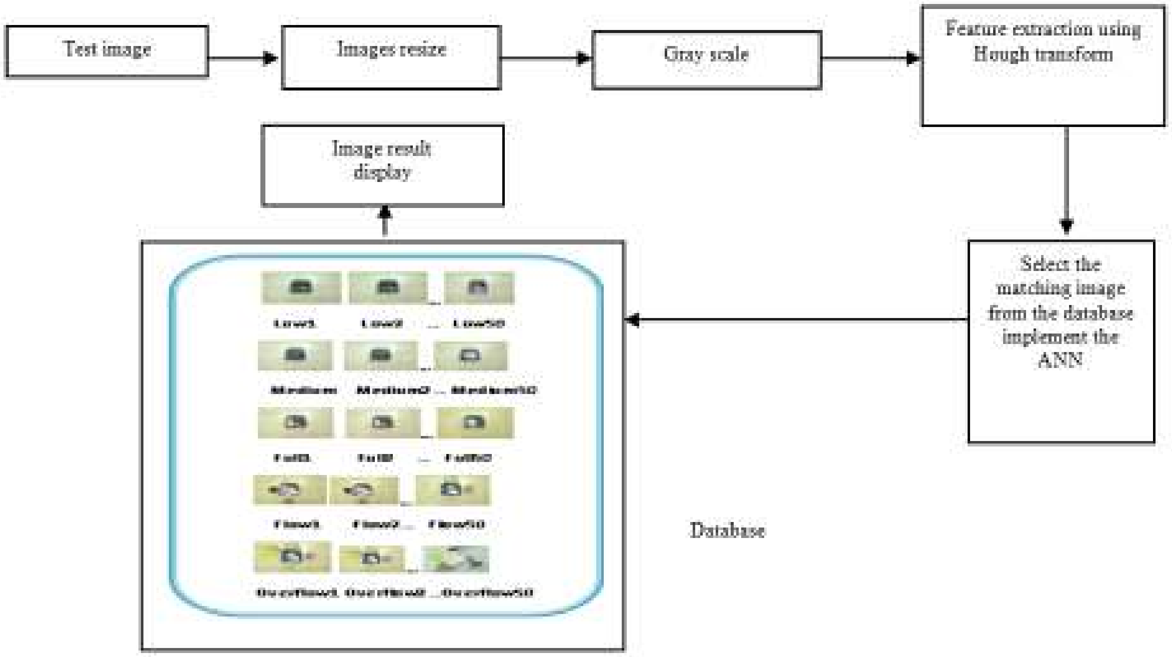

Fig. 6: FFNN Hough transforms process involved in testing image

the custom network with sum square error performance set to 'MSE' being reached as the final learning convergence criterion.

In total, 250 images, fifty images with twenty images from each group are used to train the neural network classifier; the remaining thirty images are used as test images and are classified. Once the network is trained, all the weights are saved in a test file. Figure 6 shows the process involved in testing image. The image processing is based on feature extraction using Hough transform. The FFNN are used for training and classification process, which is the image tested are matched with the references image (database) of the bin with receiving one in order to examine the status of the bin and measure the current waste that has been thrown around the bin.

RESULTS AND DISCUSSION

Performance of the FFNN classifier: The FFNN is used in the development of the classification of waste bin images. In total, 250 images, 50 images with twenty images from each group are used to test the feed forward neural network classifier; the remaining thirty images are used as test images and are twenty images for training. Once the network is trained, all the weights are saved in a test file. As a result for the training stage, twenty images from each class as used as the full set of inputs samples for training as shown in Fig. 7. As and the neural networks learns, we present the results of full set of inputs samples through the neural network to compute the sum squared error function we will use in the back propagation of errors step.

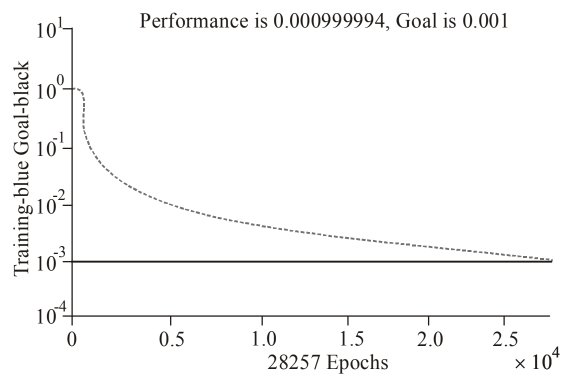

Fig. 7: Training performance of the system using FFNN

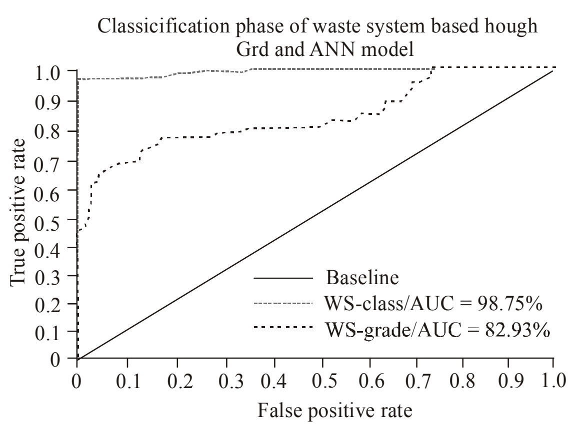

Fig. 8: Classification and grading results of system based on area under curve

To evaluate the system performance, in the ROC graph we can see the graph of the class and grade performance for waste been monitoring system. Figure 8 show the result for classification and grading of waste system based on Hough gradient and an artificial neural network model by using the Area Under the ROC (Receiver Operating Characteristic) Curve (AUC) that can measure the discriminating ability of classification model. The curves were constructed by computing the sensitivity and specify of increasing number of data finding. The larger the AUC, the higher the like hood and actual positive case will be assigned for higher positive probabilities than actual negative case. The AUC curve measure is especially useful for data sets with unbalanced target distribution. The rough guide for classifying the accuracy of the test is the traditional point system: 0.90-1 for excellent (A), 0.80-0.90 for good (B), 0.70-0.80 for fair (C), 0.60-0.70 for poor (D) and 0.50-0.60 for fail (F). From the graph and 3 ROC curves representing WS-class, WS-Grade and baseline tests plotted on the same graph, the accuracy of the test depends on how well the test separates the group being tested into WS-Class and WS-Grade. Accuracy is measured by the area under the ROC curve. An area of 1 represents a perfect test; an area of 0.5 represents a worthless test. The area under the Waste System ROC curve is WS-Class/AUC = 0.9875 or 98.75% for excellent result and for WS-Grade/AUC = 0.8293 or 82.93% for the good result. The waste system would be considered to be perfect at separating class and grade of waste.

CONCLUSION

Waste bin monitoring system has been successfully designated by using FFNN model dealing with solid waste images. And the system performance shows the efficiency used in waste classification and grading solution. The waste control center of the system provide the system to analyze image graphical, can plan better organization such as monitoring, distribution, preventive and safety. Although the motivation of this work was escalate of waste been monitoring system, the result that will obtain can applied to wide variety of local municipal authorities system.

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