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Mini Review: Artificial Neural Network Application on Fruit and Vegetables Quality Assessment

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Abstract— Recently, methods of quality assessment have gained impetus and substantial efforts have been made to develop systems regarding quality of fruits and vegetables. This paper examines latest works of using artificial neural network (ANN) for determining the quality of some selected fruit and vegetables. In this review, the theoretical background of ANN were analysed and various application of ANN intelligent method with respect to fruits and vegetables were discussed. It is intended that the arrangement and discussion of evolving method will provide direction for easy future work.

Index Terms— Artificial neural network, Quality, Accuracy, Image processing, Backpropagation neural network, Fruits and Vegetables,

1. INTRODUCTION

THE long-term aspiration of the neural-network society is to design autonomous machine intelligence but now the present usage of neural networks is in the field of pattern recognition. In the sub-field of data classification, neural-network methods have been found to be useful alternatives to statistical techniques such as those which involve regression analysis or probability density estimation. The potential utility of neural networks in the classification of imagery databases has been recognized for over a decade, and today neural networks are an established tool in the field of fruit quality classification (Du and Sun, [1]). (Barreiro et al [2], Ruiz-Altisent et al [3], kleynen et al [4], (Yacob et al [5]).

The study of techniques of prediction and diagnosis shows that the most widely used ANN is the three layers which comprises of input, hidden and output layer shown in (Figure 1). The output result relies on the weight used on the data linking the output and hidden layers. During training and learning, weights are the value which ANN works on to achieve a result that is very close to the required output (In et al [6]).

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The artificial neural networks are well known for their desirable characteristics of learning, adaptation, parallelism, generalization and fault tolerance. For the last few decades, it has been evident that ANN has significant application in fruits quality evaluation. The most important merits of multilayer perceptron (MLP) network compared to other neural model architectural are that it is simple to implement and it can perform approximation of any input-output map (In et al [6]).

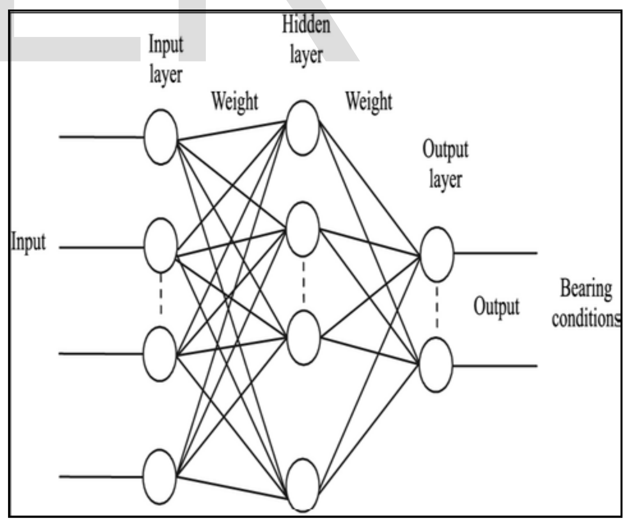

Figure 1:. Structure of Artificial Neural Networks

The purpose of ANN is to generate a network system with little errors but also yield good result from the testing data set. (Figure 2) shows the block diagram generally used for the intelligent diagnosis system. There are two types of training algorithm namely (Hecht-Nielsen,[7]; Kumar [8]).

- **Supervised:** - the target is available and the network determines the best set of weights by reducing the error between the output data and the target.

- **Unsupervised:** - only the input data set is given to the system, which then determines similar inputs without any previous knowledge.

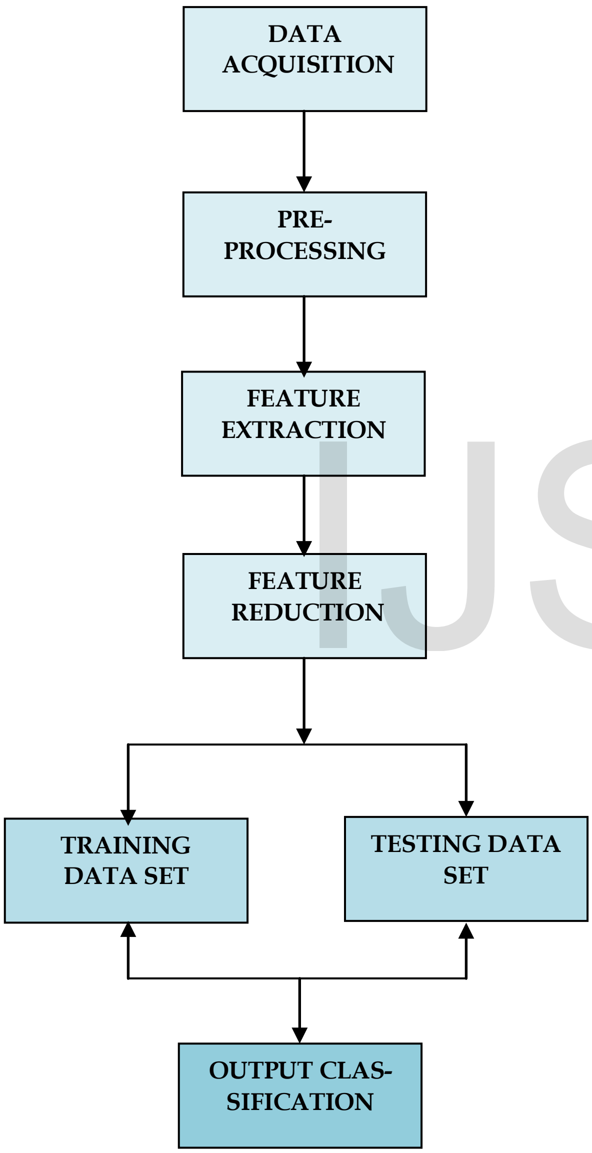

Figure 2: Block diagram of Intelligent Recognition System.

2. Backpropagation Techniques

Backpropagation neural network (BPNN) is the most commonly used ANN architecture out of the entire neural network being applied to real world problems because it can easily learn complex multidimensional mappings. It is the process by which an ANN fine-tunes the weights allocated to the linking neurons to bring the existing output data of the neuron nearer to the likely data value (Hecht-Nielsen, [7]).

It is a supervised learning mode worked based on gradient descent in error that propagates classification errors back through network and uses the errors to updates the features (Kumar, 2005). The structure of BPNN contains three layers: input, hidden, and output layers as shown in Figure 5.2. It possesses the following advantages over other statistical pattern recognition techniques (In et al., [6]).

- It has ability to handle a large quantity of heterogeneous data with great flexibility.
- It learns by example the intrinsic relationship.
- It is more fault-tolerant than conventional computational techniques
- It needs less domain-related knowledge of specific application

3. ANN for Fruits and Vegetables Quality Grading

Fruits and vegetables are growing in attractiveness in daily consumption both developing and developed countries. (Asefpour and Massah, [9]) recognized that autonomous mechanism are now effectively being deployed to determine and evaluate the quality of fruits and vegetables with the combination of digital image processing and ANN. They have successfully applied this combination to identify fungal diseases in cucumber plants by obtaining 3-textural features from the leaf images namely, energy, entropy and local homogeneity through image processing to actually determine the diseases category. The ANN structure applied was 5-20-2 network Levenberg-Marquardt (LM) backpropagation algorithm with 5-input features for energy, entropy, average temperature (AT), maximum temperature difference (MTD) and local homogeneity while the two output are hour post inoculation and diseases detection. Two hundred and fifty parameters were applied for training with thirty sets used for assessment of the model and twenty data for cross-validation. The highest accuracy occurred at correlation coefficient (R) of 0.9.

Huang, [10] developed an integrated image processing model to automate the inspection of areca nuts to identify and grade damaged crop according to either insects or diseases defect. Image acquisition and processing were performed with three colour features, one spot region (SR) and 6-geometric features extracted with region of interest identified. Normalization were applied which reduces the input parameters to value between zero and one, whereas the output was categorized into good, bad and excellent. MATLAB was used to execute the backpropagation (BPP) algorithm with random selected images applied to test the model. Classification accuracy for bad, good and excellent grades is 91.8, 89.1 and 91.7% respectively.

Zarifneshat et al., [11] assessed the application of ANN for the classification of golden delicious apple specie into healthy and bruise volume samples. Two types of multilayer algorithm, Basic Backpropagation (BB) and Backpropagation with declining learning rate factor (BDLRF) were applied with a developed MATLAB code. The inputs to the multilayer network model are five features samples such as curvature radius, temperature, acoustical stiffness, impact energy and contact force. Basic backpropagation and BDLRF learning algorithm were used to train the network model with the latter performing with higher output accuracy greater than 0.9 for R-value. Evaluation of the predicted model was done with statistical model where both gave the same level of accuracy for measured and predicted value.

Fadilah et al, [12] work shows possibility of increasing the classification accuracy of oil palm fresh fruit bunches (FFBs) by 1.66% once the number of input features to multilayer perceptron MLP neural network training model was minimized. Eighty samples of FFBs were grouped into four different classes of unripe, under ripe, overripe and ripe by a trained grade inspector. The images obtained were group into one hundred and twenty set for training, twenty eight set for validation and sixty for independent test. Two types of network technique were studied with one class applied all the fifty nine input factors, while the second class that engaged PCA only applied minimum features as the input factors. The second method yields 93.33% accuracy which led to a simple and quicker structure since minimum memory were needed for the network processing due to the decrease in input neurons number.

A multilayer feed-forward neural network model centred on 16-neurons in the hidden layer and three features at the input layers was designed to produce the highest accuracy by (Fathi, et al [13]) when applied for the purpose of predicting colour difference and mass transfer kinetics in kiwi fruits. Acquisition and analysis of images obtained from computer vision system were performed and computed as an input to the neural network for assessment diverse structures using 2-20 neurons in the hidden layer. The most accurate model for predicting water loss, colour images and solid gain occurred at sixteen neurons hidden layer with lowest mean square error (MSE) and high R-values of 1.005, 2.312, 2.137 and 0.92, 0.994, 0.88 respectively. These acquired R-value finally correlate with the experimental values obtained.

Balbay et al. [14] introduced the application of ANN training model during drying procedure of siirt pistachios to predict the moisture content (MC) and drying time (DT) using a fixed bed dryer. Different experiments were carried out so as to acquire information for MC in relation to DT at a distinct temperatures and velocities. The ANN model applied two hundred and seven data sets with the following number of neurons 7, 15, 25 and 30 at the hidden layer. Two variants were applied to achieve optimization with Levenberg-Marquardt (LM) gave best performance as against Scaled Conjugate Gradient (SCG) backpropagation at 0.3692, 0.9996 (LM at 15 neurons) and 0.4459, 0.9993 (SCG at 25 neurons) for RMS and coefficient of multiple determinations values (R) respectively.

Fathi et al, [15] used an intelligent system ANN and genetic algorithm (GA) for predicting shrinkage level of dried kiwi fruits based on Fractal theory. The image acquisitions were performed on different dried samples at a corresponding temperature and ImagJ software was used to determine fractal parameters of the fruit samples based on box counting method. Using as input parameters the moisture content (MC) with background interface line and level of samples shrinkage as an output of genetic algorithm, an optimization was achieved at seventeen neurons value and correlation coefficient (R^2) of 0.95.

Mohebbi et al, [16] proposed ANN and genetic algorithm (GA) model that can forecast moisture content (MC) of banana dried by means of ultrasound rays and osmotic dehydration. There are one output MC and 6- input parameters namely pre-treatment, type of sugar, solution or osmotic concentration, drying temperature, drying time and pre-treatment time to the network model. The best performance using GA illustrate that the most sensitive input parameters are drying temperature and time with R -value of 0.94.

Efficient combination of colour and texture features for fruit recognition have been carried out with the minimum distance classifier based on the statistical and co-occurrence features derived from the Wavelet transformed sub-bands. This method is commonly applied as a class of techniques for segmenting out region of interest in an image. Background subtraction is derived from the subtraction of the observed image from the estimated image and thresholding the result to generate the images of interest. Finally, training and classification were applied using Minimum Distance Classifier (Arivazhagan et al, [17])

Earlier research work was able to forecast respiration rate of fruits and vegetables based on exterior variables only successfully. However, (Wang et al, [18]) demonstrated that the effects of internal parameters of fresh papaya on the amount of consumed oxygen and formation level of carbon dioxide could be determined and evaluate by applying ANN and regression technique. The four internal parameters considered for input are temperature, maturity, oxygen and carbon dioxide, while oxygen and carbon dioxide were considered for the output. The regression model applying second order polynomial gave very small precision compared to ANN of four input, fifteen hidden neurons and two output layers trained by Levenberg-Marquardt algorithm (LM) which gave higher accuracy of R-value of 0.988, 0.987 for carbon dioxide and oxygen respectively.

Zhou et al, [19] developed a modified backpropagation algorithm to detect spot created by infection of disease on twenty samples of rice. A backpropagation neural network (BPNN) architecture of 5-10-1 network was used with H, I3b and three

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RGB colour space chosen as input parameters and output based on either one which symbolizes good leaf or zero signify defective leaf. The method entails the evaluation of images segmented automatically against the one done manually which uses white to represent defective spot and black as zero to stand for non-defective area. Classification accuracy of 99.8% was attained for both standard and improved BPNN model.

Automatic fruits identification systems with the combination of Fourier descriptors, artificial neural network and spatial domain analysis were proposed. The colour and shape information obtained from digital camera images of fruit samples were used as input to ANN training for fruit sorting and identification purpose by (Aibinu et al,[20]). The application of neural network model to predict the vase life of cut roses planted in a greenhouse showed that the ANN is better in prediction than traditional statistical techniques (In et al., [6])

Yacob et al, [21] performed detection and grading of Harum Manis Mango weevil defect with the aid of dielectric sensor trained with neural network backpropagation. The procedure was repeated for data acquisition collected from thirty samples out of which sixteen samples were used for training and fourteen samples for testing. The training and testing started from the upper to lower epochs. They reported that B training set has higher rate of performance than set A and C at a learning rate of 0.01 corresponding to the least Mean square error (MSE) of 0.0870.

Huang [22] reported classification accuracy of 89.6 and 97.2% for model with Phalaenopsis diseases infected seedling and model without diseases respectively. Image processing were applied to extract three colour parameters (RGB) and eighteen textures features from identified three types of diseases.

Artificial neural network and colour image processing was employed by Mohebbi et al, [23] to assess the level of moisture in a dried shrimp. Six colour features were used to train ANN and shows that optimization occur at 5-neurons hidden layer. They obtained an accuracy of R^2 value equals to 0.86 which indicates neural network combined with image processing could predict the moisture content of fruits.

Moshou et al, [24] developed an intelligent system that was able to classify different reflectance generated from an optic devices for yellow rust diseases infected wheat plant and good samples. Image processing techniques were applied and classification methods were developed from two main neural network technology such as multilayer perceptrons (MLP) and self organising Maps (SOM). The neural network model gave better accuracy of 99% compared to quadratic discriminating technique which yield 95% accuracy.

Summary of fruit and vegetables that have been assessed with intelligent method are shown in Table 1.

Table 1: Summary of Different Fruits and Vegetables Assessed with Intelligent Techniques

Sample	Description	References
Wheat	Intelligent classification of different reflectance generated for yellow rust diseases infected samples. Neural network model gave better accuracy of 99%.	Moshou et al. (2004)
Phalaenopsis	Image processing for diseases classification. Accuracy of 89.6 and 97.2% for model with diseases infected seedling and without diseases respectively.	Huang (2007)
Shrimp	Assessed the level of moisture using ANN and colour image processing. Six colour features were used for training. Accuracy of R^2 = 0.86 was achieved.	Mohebbi et al. (2007)
Mango	Detected and grade weevil defect with the aid of dielectric sensor trained with BPNN. The training and testing started from upper epochs to lower epochs. B training set has higher accuracy than set A and C at a learning rate of 0.01 corresponding to MSE of 0.0870.	Yacob et al. (2008)
Rice	Modified backpropagation algorithm to detect spot of disease on twenty samples. BPNN architecture of 5-10-1 network was used with classification accuracy of 99.8%.	Y. Zhou et al. (2010)
Papaya	Demonstrate that the effects of internal parameters on the amount of consumed oxygen and formation of carbon dioxide using ANN and regression technique. LM gave higher accuracy of R value of 0.988, 0.987 for carbon dioxide and for oxygen respectively compared to regression model.	Wang et al. (2010)
Kiwi	Intelligent system for predicting shrinkage level with	Fathi et al. (2011)

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	input parameters as MC and background interface line with level of samples shrinkage as an output of GA, an optimization occurred at 17 neurons value with R^2 value of 0.95.	
Pistachios	Designed and construct training model for drying procedure of shelled pistachios. LM gave best performance at RMS = 0.3692, R = 0.9996 and hidden neurons = 15 compared to SCG backpropagation	Balbay et al. (2011)
Banana	Forecasting the MC of dried samples using ANN and GA model that was dried with ultrasound rays and osmotic dehydration. Performance illustrate that the most sensitivity input parameters are drying temperature and time with R = 0.94	Mohebbat Mohebbi et al. (2011)
Kiwi	Predicting colour difference and mass transfer kinetics occurred at sixteen neurons hidden layer with lowest MSE and high R-values of 1.005, 2.312, 2.137 and 0.92, 0.994, 0.88 respectively.	Fathi et al. (2011)
Oil palm	Classification accuracy of FFBs increased by 1.66% once the input features to MLP neural network training model were minimized.	Fadilah et al. (2012)
Apple	Classification into healthy and bruise volume. BDLRF learning algorithm performed with higher output accuracy than BB.	Zarifneshat et al. (2012)
Areca nuts	Identify and grade damaged crop according to either insects or diseases defect. BPP algorithm with classification accuracy for bad, good and excellent grades as 91.8, 89.1 and 91.7% respectively.	Huang (2012)
Cucumber	Identify fungal diseases in cucumber plants by obtaining 3-textural features from the leaf images. 5-20-2 network LM BBP algorithm gave highest accuracy with R- value of 0.9.	Asefpour Vakilian & Massah (2013)

4. CONCLUSION

Determination of quality of any food material is actually a complex problem but ANN technique is highly accurate and cost effective due to its computerised and intelligent capability. Medically, the intelligent image processing technique has showed to be useful for human diseases diagnoses and which therefore shown, can easily be adopted for defect detection/prediction of fruits and vegetables quality. This technique would be very valuable in the inspection of materials of variable shapes usually encountered in the agricultural and food industry. Researcher must keep focusing on making intelligent systems use easier and lowering the price to make it within the reach of common entrepreneur.

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