Neural Estimation of Food Age with Adaline-based Multi-Layer Perceptron

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Abstract: This study employs a 4-input and 1-output feedforward neural network with adalines used to implement learning via error back-propagation (EBP) using least mean square rule. The neural network is used to predict the condition of both cooked and uncooked food as well as fresh vegetables by determining food age (in days). Neurosolutions training software is used to simulate the neural network. Training data is obtained from a constructed metal oxide semiconductor (MOS) ammonia circuit. Results show that a 95% overall accuracy of neural network results is obtained. This demonstrates the capability of neural networks in accurate classification of sample data points. Food samples used to obtain inference database include rice, beans, fresh vegetables, yam and potatoes.

Keywords/Index Terms: neural network, supervised learning, back propagation, e-nose, artificial intelligence

1. Introduction

The advent of neural networks began in the early 1940's when Warren McCulloch and Walter Pitts posited that the behavior of biological neurons could be modeled in the form of propositional logic (McCulloch & Pitts, 1943). In essence, they concluded that the degree of accuracy of a neuron network is directly proportional to the degree of accuracy of the temporal propositional expressions (TPEs) describing it. This idea led to the creation of the artificial neural network (ANN). Since then, ANNs have been successfully used to predict trends in marketing and economics, as well as recognize data patterns in meteorology, medicine, science and technology. The field of neural networks has experienced many advances since 1960, when two of the earliest feedforward neural network algorithms were introduced. These were the least mean square algorithm by Widrow and Hoff in 1960 and the perceptron rule by Rosenblatt in 1962 (Widrow & Lehr, 1995). Madaline Rule I was the earliest learning rule for feedforward networks with multiple adaptive elements. Paul Werbos extended this discovery in 1971 by developing the back propagation algorithm for multilayer neural networks. The discovery of back propagation has made it possible to employ neural networks in non-linear, high-precision problems (Widrow & Lehr, 1995). Back propagation neural networks have successfully been used in vehicle autonomy, expert systems, speech recognition and so on.

An artificial neural network has a structure similar to that of the biological neuron which consists of a soma (body of the neuron) and an axon (receptor). Neurons send and receive signals to and from each other via a structure called synapse. These synaptic signals can be either excitatory or inhibitory. Each neuron has a signal threshold which has to be overcome in order for excitation to occur within the neuron. The threshold varies from neuron to neuron which makes its value non-deterministic in nature. McCulloch and Pitts attribute this non-linear nature to either synaptic irreciprocity or varying neural anatomical configurations (McCulloch & Pitts, 1943). There are cases in which an applied stimulus does not excite a particular neuron even when the signal is increased to maximum value. In such cases, the neuron is said to exhibit neural inhibition. Inhibition could be either relative or absolute.

Ammonia is a volatile organic compound (VOC) which is present in nearly all biological matter and has been used as a measure of bacterial or microbial activity in both plants and animals. As a result, it can be used to measure the extent of decay of organic materials depending on the level of its concentration within them. Ammonia is also found in minute quantities in the atmosphere as a result of the decay of plant and animal matter. This decay process is called putrefaction and describes the decomposition of proteins due to bacterial or fungal action. This work investigates the use of an ANN to predict the age of food by estimating the concentration of ammonia in the food samples. The results of the work aim to realize a real-time monitoring system which could be adopted by farmers and other food-based organizations to monitor the condition of food while in storage. 50% of farming households, 30% of rural households and 20% of urban households across Africa still experience food insecurity as a result of food spoilage during storage (Mwaniki, 2004). The results of the work would help to reduce food insecurity caused by spoilage which is a huge problem both within Africa and the world as a whole.

An adaline (adaptive linear network) is a single-layer neural network consisting of a weight, a bias and a summation function. It differs from the McCulloch-Pitts perceptron in the sense that weights are adjusted according to the weighted sum of inputs in the former, whereas in the latter, the total input is passed to the transfer function while the function's output is used for adjusting weights. In single-element neural networks, adaptive algorithms such as LMS or perceptron rule are used to adjust adaline weights to respond accurately to as many patterns as possible in a training set with binary desired responses (Widrow & Lehr, 1990). Once the weights are adjusted, responses of the trained element can be tested by applying various input patterns. Correct response to input patterns not included in the training set demonstrates that adalines are capable of generalization. The adaline's structure is shown in Fig. 1. A multi-layer perceptron (MLP) is a neural network structure consisting of at least one hidden (process) layer. MLPs are particularly suited for cases involving complex data classification. This is because multiple process layers help to avoid the problem of premature convergence associated with such cases. A madaline consists of several adaptive linear neurons and is shown in Fig. 2.

The metal oxide semiconductor (MOS) sensors have been used in the past for many sensing applications. For example, see the review by Huang and Wan (Huang & Wan, 2009) and also Arshak *et al* (Arshak, K. et al, 2004). There are many semiconducting metal oxides that are known to respond to various gases and other volatile organic compounds. These therefore have been used widely in food industries (Ray, 2005; Kizil & Lindley, 2009), medical applications (Kodogiannis, V.S. et al, 2008), agriculture (Persaud, K.C. et al, 1994), detection of hazardous gases (Noorsal & Sidek, 2004) and many other applications (Berna, 2010; Pawar et al, 2012). However, in spite of this wide application one of the greatest challenges facing electronic nose (e-nose) designs is that of cost. Most forms of the e-nose that have been successfully implemented are too expensive for use by the general public. As a result, their widespread use has been severely limited. The e-nose proposed in this article has been designed to address this limitation. The components in the sensor's circuitry are affordable compared to most of the existing implementations. The MOS sensor used in this work detects ammonia concentration in the parts per million (ppm) range.

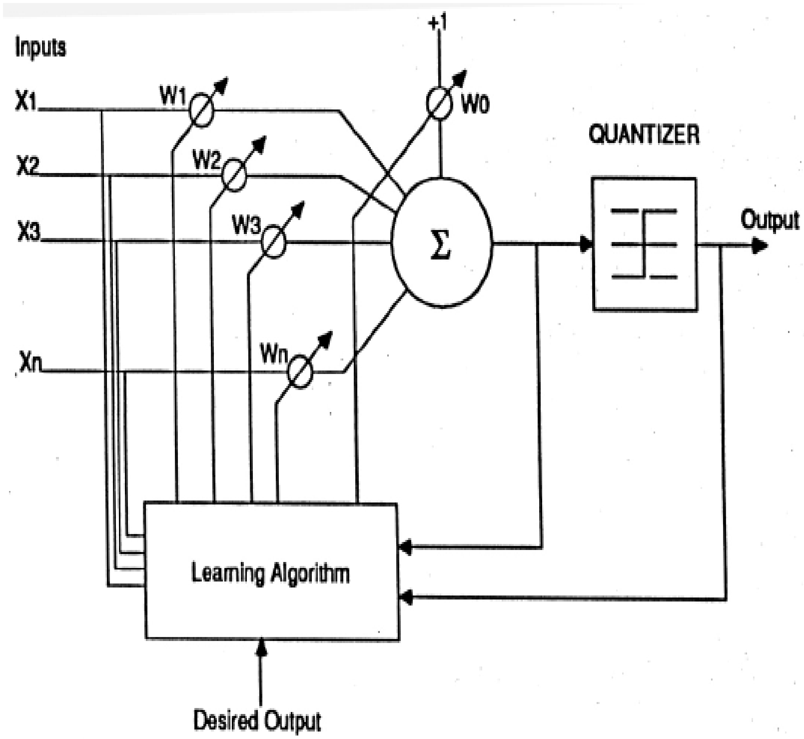

Figure 1. Adaptive linear neuron (Mehrotra, Mohan, & Ranka, 2003)

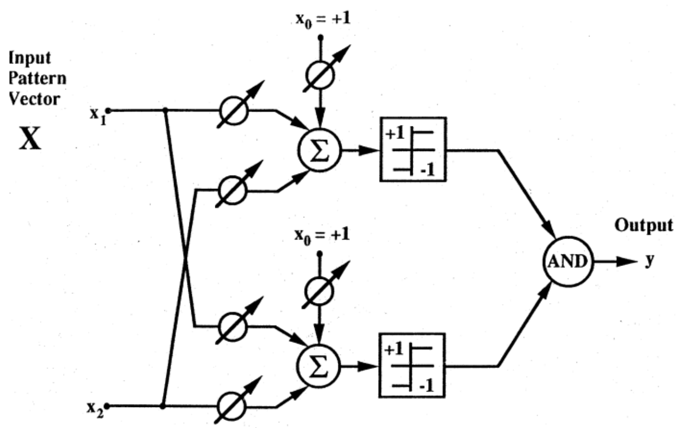

Figure 2. Madaline consisting of 2 adalines (Widrow & Lehr, Perceptrons, Adalines and Backpropagation, 1995)

2. Methodology

Adaline weights are adjusted according to the Widrow-Hoff learning rule, also known as the LMS rule. This is represented mathematically as:

$$w_{g,h} : w_{g,h} + \eta(t-a)x \qquad (1)$$

From (1), g and h are any two interconnected adalines, η is the learning rate, t and a are the target and actual adaline outputs. The adaline converges to the least square error given by:

$$E = (t-a)^2 \qquad (2)$$

Equation (2) represents the gradient descent update for linear regression and is justified by the following:

$$\frac{\partial E}{\partial w} = \frac{\partial (t-a)^2}{\partial w} = 2(t-a)x \qquad (3)$$

Equation (3) shows that moving in direction of $(t-a)x$ increases error while moving in the opposite direction decreases error. This scenario presents a kind of hill-climbing approach to obtaining the best possible solution. Fig. 3 shows the form of error landscape in the weight space.

The aim of LMS is to minimize the mean square error (MSE) according to the following:

$$MSE = \frac{1}{n}\sum_{j=1}^{n} e(j)^2 = \frac{1}{n}\sum_{j=1}^{n}(t(j) - a(j))^2$$

(4)

The following steps summarize the adaline's learning procedure:

(i) Initializing the network and threshold weights ($w_1 .... w_n$) and w_t . This involves setting both network and threshold weights to small bipolar random values

(ii) The new input vector $x_1, x_2, ...x_n$ and the target output $t(j)$ are presented. x_0 is a fixed bias with a value of 1, while $t(j)$ can be ± 1.

(iii) the actual output $a(t)$ is obtained according to:

$$a(t) = \Gamma[\sum_{i=0}^{n} w_i(t) * x_i(t)] \qquad (5)$$

From (5), $\Gamma(E) = 1 \; when \; E > 0 \; and \; -1 \; when \; E \leq 0.$

(iv) Adaptation of weights according to

$$w_i(t+1) = w_i(t) + \eta[t(j) - \sum_{i=1}^{n} w_i(t)x_i(t)]x_i(t)$$

(6)

Steps (ii) to (iv) are repeated until the target outputs and actual network outputs are all equal for all input vectors of the training set.

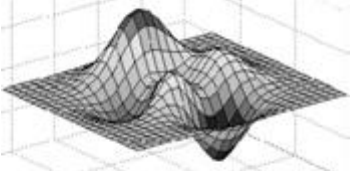

Figure 3. Error landscape in weight space (Mehrotra, Mohan, & Ranka, 2003)

The LMS algorithm therefore chooses a random input-output pair from the training data set. The neural network then operates on the input to generate a corresponding output. This output is used to compute the output error between the target and actual outputs. Weights are then adjusted according to the input and error vectors, after which another random pair is selected and the error correction process repeated. Stopping criteria is checked at the end of each epoch. The stopping criteria may be a preset number of epochs or a threshold error value. In this work, the stopping criterion is the degree of similarity between training and cross-validation data. Neurosolutions training software performs cross-validation by splitting the entire data into a number of subsets of equal size. Each subset is used for testing and the remainder for training. The error estimates are averaged to yield an overall error estimate. In this work, half of the data is used for training and the other half is used for testing to maintain network symmetry. The algorithm below summarizes the LMS approach.

Network training begins with randomly chosen initial weight values (between -1.0 and 1.0) (Mehrotra, Mohan, & Ranka, 2003). Larger magnitudes may drive hidden layer node outputs to saturation, thus requiring long training time to emerge from saturation. The learning rate η is varied by increasing its value at iterations that improve network performance significantly and decreasing it at iterations which worsen performance significantly. Iteration range is typically between 0.1 and 0.8. Two hidden layers are used in order to further reduce likelihood of premature convergence. The overall structure of the neural network is shown in fig. 4.

Training data points are obtained from a sensor circuit with ammonia sensitivity of 0.033V/ppm (parts per million). The sensor is the metal oxide semiconductor (MOS) type. Neurosolutions software was used in training and testing of the neural network's results for both cooked and uncooked food samples. Neural network training and testing points were obtained from the following relation:

$$Sample\ po\mathrm{int}(S_p) = \frac{ammonia\,concentration\,of\ test\ po\mathrm{int}}{60\,ppm}$$

(7)

60ppm was chosen because testing was limited to a maximum of 150 days. This concentration was observed for food samples 150 days and older.

Algorithm 1:

While MSE is undesirable and iterative boundaries are not exceeded,
do
for each input pattern $i_p : 1 < p < N$,
compute hidden node inputs;
compute hidden node outputs;
compute inputs to output nodes;
compute network outputs;

compute error btw actual and desired
outputs;
modify weights btw hidden and
output nodes;
modify weights btw input and hidden
nodes;
end for
end

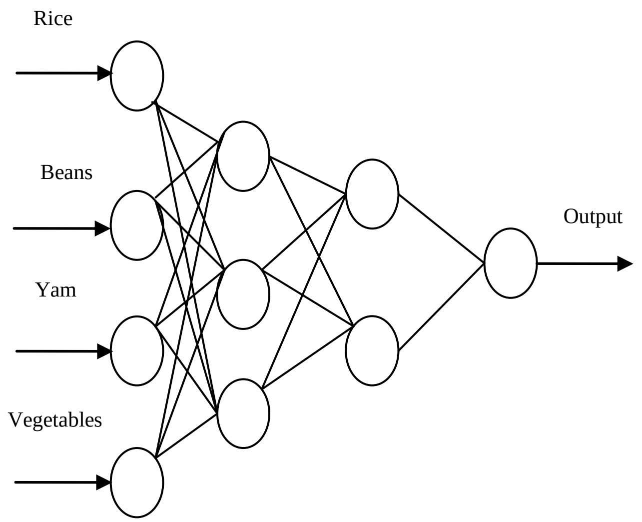

Figure 4. Adaline-based neural network structure

The network shown in fig. 4 has an activation (threshold) function described by a sigmoid transfer function. The sigmoid function is used because the behavior of ammonia sample points is semi-linear as build-up of ammonia is concerned. The behavior for both fresh and decayed samples is almost exponential as given by the function:

$$f(x) = \frac{1}{1 + e^{-\sum_i w_i x_i}} \quad (8)$$

The ammonia sensor resistance is obtained according to:

$$R_{sensor} = \frac{V_{supply} - V_{output}}{V_{output}} \times R_{load} \quad (9)$$

Equation (9) is used to obtain the sensor's ammonia sensitivity which is used to determine the concentration of individual test points for the different food types. Fig. 5 shows the constructed sensor circuit.

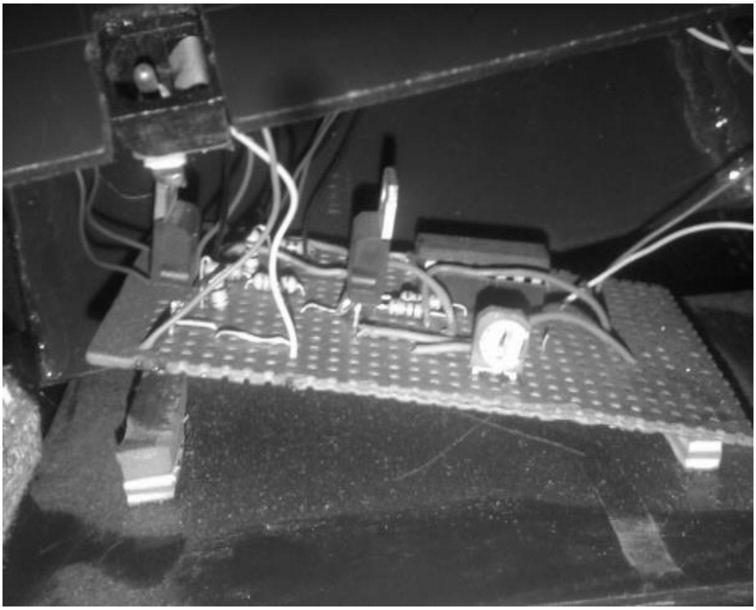

Figure 5. Constructed ammonia sensor circuit

3.Results and Discussion

The NeuroSolutions training network is shown in figure 5. The training breadboard shows the sigmoid transfer function being applied to the process layers. Data samples are entered to the neural network as an Excel spreadsheet. The training software allows specification of the training-t0-cross-validation data ratio. However, this ratio should not be too high to allow the network to determine how well it has learnt; neither should it be too low to avoid false convergence. Separate training sessions were performed for cooked and uncooked food samples as well as fresh vegetables respectively. Ten (10) training sessions were performed for each set of food samples with 50 test points per training session. Successful training outcomes for all sets of samples are shown in tables 2, 3 and 4. From results obtained, it can be seen that for all food samples tested, ammonia concentration increases as food samples advance in age. Table 2 shows that ammonia content in cooked food samples increased drastically as the samples aged beyond 2 days (5.10ppm to 21.36ppm). This is due to increased microbial activity in cooked food especially for the beans samples which had high protein content. A maximum ammonia concentration of about 25ppm was obtained for cooked food samples. Neural network results for uncooked food samples are shown in table 3. It was observed that ammonia concentration in these samples is less than those of cooked food samples. For instance, a yam sample at 60 days old had ammonia concentration of 4.68ppm while the same sample in cooked form had 5.10ppm concentration at only 2 days old.

Vegetables had the highest values of ammonia content with 37.92ppm being obtained for 7-day old samples. It should be noted that testing was carried out without refrigeration of any food samples. The classification accuracy of the neural network for the three classes of samples (cooked, uncooked and vegetables) is summarised in table 4. An overall classification accuracy of 95% demonstrates that the selected neural network architecture is reliable in terms of using ammonia content to determine food age. Incorrect results are attributed to the subjective selection of learning rate η and internal weight assignment especially between the two process layers.

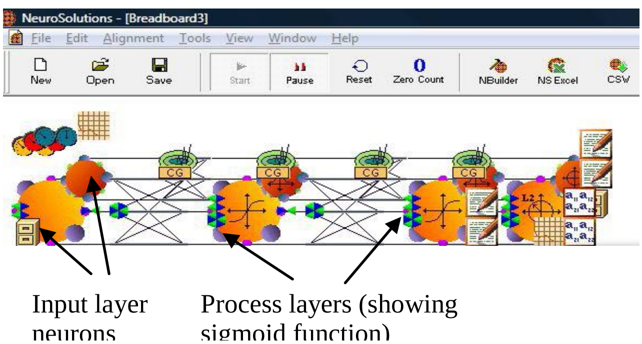

Figure 5. Neuro Solutions Simulation Breadboard

Table I. Neural simulation of cooked food samples (rice, beans, yam, and potatoes)

Training session	Neural Network output	Ammonia concentration (ppm)	Food age (days)
1	0.017, 0.050	1.02 – 3.00	0 – 2
2	0.021, 0.048	1.26 – 2.88	0 – 2
3	0.015, 0.012	0.72 – 0.90	0 – 2
4	0.045, 0.020	1.20 – 2.70	0 – 2
5	0.061, 0.085	3.66 – 5.10	0 – 2
6	0.40,	21.36 – 24.00	3 – 5

	0.356		
7	0.390, 0.413	23.40 – 24.78	3 – 5
8	0.415, 0.514	24.90 – 30.84	3 – 5
9	0.350, 0.398	21.00 – 23.88	3 – 5
10	0.417, 0.303	18.18 – 25.02	3 - 5

Table II**.** Neural simulation of uncooked food samples (rice, beans, yam, and potatoes)

Training session	Neural Network output	Ammonia concentration (ppm)	Food age (days)
1	0.073, 0.044	2.64 – 4.38	0 - 60
2	0.065, 0.040	2.40 – 4.00	0 -60
3	0.088, 0.091	5.28 – 5.46	0 - 60
4	0.097, 0.102	5.82 – 6.12	0 – 60
5	0.050, 0.078	3.00 – 4.68	0 – 60
6	0.083, 0.092	4.98 – 5.52	61 – 150
7	0.116, 0.101	6.06 – 6.96	61 - 150
8	0.122, 0.104	6.24 – 7.32	61 - 150
9	0.111, 0.106	6.36 – 6.66	61 – 150
10	0.113, 0.119	6.78 – 7.14	61 - 150

Table III. Neural simulation of fresh vegetables (cabbage, lettuce and carrots)

Training session	Neural Network output	Ammonia concentration (ppm)	Food age (days)
1	0.050, 0.113	3.00 – 6.78	0 - 3
2	0.092, 0.108	5.52 – 6.48	0 - 3
3	0.099, 0.112	5.94 – 6.72	0 – 3
4	0.108, 0.116	6.48 – 6.96	0 – 3
5	0.089, 0.101	5.34 – 6.06	0 – 3
6	0.253, 0.305	15.18 – 18.3	4 – 7
7	0.362, 0.486	21.72 – 29.16	4 - 7
8	0.549, 0.628	32.94 – 37.68	4 – 7
9	0.636, 0.645	38.16 – 38.70	4 – 7
10	0.608 , 0.632	36.48 – 37.92	4 - 7

Table IV. Overall Accuracy of Neural Simulation

	Correct (%)	Incorrect (%)	Accuracy (%)
Cooked	94	6	94.0
Uncooked	96	4	96.0
Vegetables	95	5	95.0
Average Overall accuracy			**95.0**

4. Conclusion

The obtained simulation results demonstrate that neural networks are capable of data classification to a high degree of accuracy when network parameters are well selected. Inaccuracies arise when network parameters are not well chosen. In this case, the network becomes saturated and therefore fails to converge. This observation informed the use of two process layers in the adopted neural network model to provide adequate time for the network to settle and eventually converge. The learning rate was closely monitored to also prevent premature convergence. The technique of cross-validation applied to the training data also increased the accuracy of classification results. It has also been observed that ammonia concentration increases rapidly in cooked and protein-based food samples when compared with uncooked samples. Vegetable samples had the highest ammonia content. Further work will concentrate on improving network accuracy by determining a more objective approach to learning rate and internal weight manipulation.

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