Multi-criteria inventory classification for retailers using Artificial Neural Network

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ABSTRACT

This paper presents an artificial neural network technique which is used for classification of multi-criteria inventory for retailers. The control of large inventory items is not possible for maximum profit with an equal attention. Generally, single criteria inventory classification is followed by inventory manager such as total cost. It has been realized that for retail organizations the single criteria inventory classification is less effective, So, instead of cost, there are some other criteria which are more important, which are profit per unit, demand of the item, shelf-life, of the item and lead time to the store. So a multi-criteria approach has been used here for inventory classification of retail outlets. For this purpose, the artificial neural network technique has been used the classification of inventory has carried out by pattern recognition and classification tool in MATLAB software. For training, the network scaled conjugate gradient backpropagation is used in this work. So, a classifier model is trained for the classification of multi-criteria inventory and prediction of inventory based on an expert system which can classify any number of items in retail outlets.

Keywords— Artificial neural network, MATLAB, pattern recognition and classification tool, scaled conjugate gradient backpropagation

1. INTRODUCTION

For the success of supply any organization an effective Inventory Management has played an important role [1]. The reason for carrying the inventories is to maintain a balance between organization and customers. So, the effective management of these inventories is essential to ensure optimal stock levels of any industry. Inventory represents an investment of an organization that is tied up until either the item is sold or used [2].

Generally, the number of inventory items is so large that it becomes very difficult to effectively manage all the items by giving equal attention to each of them [3]. Sometimes, only one criterion is not a very effective measure of decision-making. To tackle this problem, multiple criteria decision-making methods are used. So, the inventory items are normally classified into a few groups based on some criteria. By this classification, the most important items get separated from other less important items. Also, proper control policies can be applied to different groups based on their importance. Using this approach, stock-out of highly important items can always be avoided by having good control over their inventory.

There are many techniques are used for classification of inventory in industries but. ABC inventory classification is a widely used inefficient planning and control method. ABC analysis is the most widely used technique in inventory management to categorize an extent number of inventory items into three categories namely A, B, And C. As per Pareto hypothesis (This 80/20 rule is known as the Pareto principle [4], which is why this method is sometimes called Pareto analysis.), category A (contains the very important items), category B (includes the moderately important items) and category C (contains the relatively less important items)[6]. The alternative term ABC analysis stems from the fact that the first about 20% of important items are known as Category A items, the next, typically about 30% are Category B items and the relatively less important, though larger in number, about 50% are Category C items [5]. The main aim of this technique is to manage the inventory items in an effective way. In this way, the cost of inventory has been under control.

So this work suggests a new approach to profit based multi-criteria inventory classification for retail outlets using the classifier model. The demand for the product, Shelf life and Lead time are the other important criteria which have been used performing the classification.

2. ARTIFICIAL NEURAL NETWORK

2.1 Artificial Neural Network

Artificial neural network (ANN) is a soft computational nonlinear mapping structure or information processing paradigm inspired by a biological nervous system such as the brain, process information [4]. Neural Network is just a complex system of interconnected neurons which are millions and millions in number. The first model of a neuron/ biological model was described or formulated by McCulloch and Walter Pitts in 1943 as a physiologist, with one output and two inputs, modelled neuron. They realized that the neuron would not become active with only one input active [7].

The neural network is a biological cell that process information, with the help of some electrical and chemical changes, from one neuron to another neuron. In a biological neuron network, the neuron is individual cells which receive input from a sensing cell/neurons and then send an output to other cells/neuron that is connected to it [8]. A biological/human Neuron consists of synapses, cell body/soma, axon and the dendrites. The soma/cell body has a nucleus for contains information about hereditary traits and plasma.
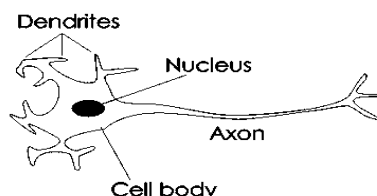

Fig. 1: Biological neural network system [9]

  (a) Dendrites: Dendrites are extensions of a neuron-like hair, and each dendrite gives some input to the neuron which inputs are given to the soma. So through dendrites, a neuron receives signals from another neuron.
  (b) Soma: soma have the responsibility of processing for inputs, and the output is provided through the axon and synapses to another neuron.
  (c) Axon: The axon carrying the output which is received to other neurons, through the synapses.
  (d) Synapses: Connection between two neurons takes place at the synapses so Synapses connected to the dendrites of neurons in the next layer. Because of synapses and dendrites, the connections between neurons are possible [8].

Generally, the artificial neural network consists of a number of interconnected processing elements, called neurons with three simple elements: multiplication (inputs and weights), summation (summation of all product of input and weights) and activation (defines the output of sets of input).
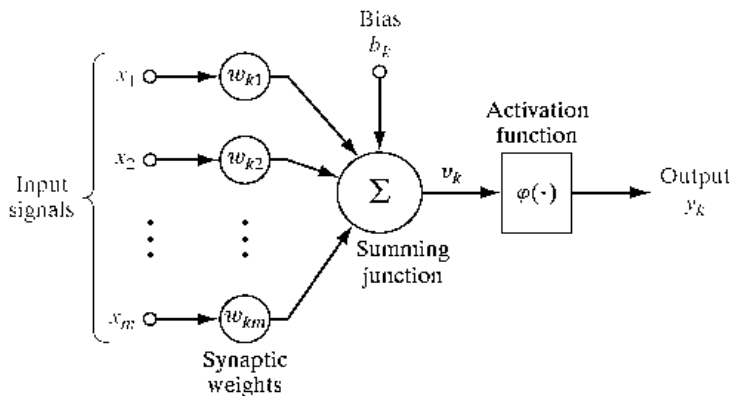

Fig. 2: Artificial neural network system [10]

Every input value x (k) is multiplied with individual weight w (k) at the entrance of artificial neuron, and at the summation section, the sum occurs of all weighted inputs and bias b (k), of an artificial neuron. At the exit/output y (k) section of artificial neuron the sum of weighted inputs and bias is passing through activation function/ transfer function φ (y). So the output of a neuron is finally evaluated by an activation function φ (y), [11]

$$Y(K) = \varphi\left(\sum_{I=0}^{M} W_I(K) \cdot X_I(K) + b\right) \tag{1}$$

2.2 Activation Functions

The activation function, in terms of the induced local field, defines the output of a neuron. The activation functions apply for the input to get the exact output. There are two types of activation function are identified as follows

2.2.1 Threshold Function: The output is set at one of two levels, depending on whether the total input is greater than or less than some threshold value.

$$F(X) = \begin{cases} 0 & x < 0 \\ 1 & x \geq 0 \end{cases} \tag{2}$$

Sigmoid Activation Function: This function has two types as follows:

• **Binary sigmoidal function:** The binary sigmoid activation function, positive in nature, carry out input between 0 and 1. So output cannot be less than 0 and more than 1. It can be defined as:

$$F(X) = \text{sigm}(X) = \frac{1}{1 + \exp(-x)} \tag{3}$$

Bipolar sigmoidal function: The Bipolar sigmoid activation function, can be positive or negative in nature, carry out between -1 and 1. So its output cannot be less than -1 and more than 1. It can be defined as [10]

$$F(X) = \text{sigm}(X) = \frac{2}{1 + \exp(-x)} - 1 = \frac{1 - \exp(x)}{1 + \exp(x)} \tag{4}$$

2.2.2 Softmax function: Softmax required normalized datasets in the scale of [0, 1] because the Softmax function operates in range 0s and 1s. Also, the sum of the Softmax outputs is always equal to 1. So, neural networks model classifies the instance as a class that has an index of the maximum output. [12].

$$\sigma(y_i) = \frac{e^{y_i}}{\sum_i e^{y_j}} \tag{5}$$

Where i = 1 to n and j = 1 to n

3. METHODOLOGY
In this work, four factors were considered for improves the effectiveness of classification which was, profit per unit, the demand of item and lead time and shelf life of the item. The demand for an item and lead time are a very important consideration for classification [13]. Shelf-life based policies improve the overall performance of the supply chain. So shelf life is more important criteria for inventory classification [4].

3.1 Acquiring Input Data
This work has been carried out using data obtained from a retail outlet which located in Jaipur, Rajasthan, India by conducting the survey. An approximate value has been used in this work because most retail outlets were very reluctant in providing actual data. Each data sets contained four attributes such as profit (Rs. /unit), demand (units/week), shelf life (days), and lead time (days). The constructed survey format for data sets is shown as in figure 3.

Data Collection					
Purpose: Data collection for constructing a database for training and testing the neural network					
Retail Store/Outlet Name:					
Retail Store/Outlet Address:					
Survey Conducted by:					
S. no.	Product Name/ID	Demand (Units/week)	Profit (Rs./Unit)	Lead Time (Days)	Shelf-Life (Days)

Fig. 3: Constructed survey format for datasets

3.2 Normalization of data
The values of input variable would have a large range so they directly used but the activation function of the artificial neural network operates optimally in a small range in 0s to 1s shown in table 1 for the sample. Thus avoid this problem the normalization is must require for optimum result. So here three criteria (profit, demand and shelf life) were normalized, considering larger is better, by the formulas as below:

Normalization of datasets for considering Large is better
Normalized = (x-min(x))/ (max(x)-min(x))
Normalization of datasets for considering Smaller is better
Normalized = (max(x)-x)/ (max(x)-min(x)).

Table 1: Normalized input datasets to the train the network

S. no.	Profit (Rs./Unit)	Demand (Units/week)	Lead Time (Days)	Shelf-Life (Days)
1	0.0243	0.5632	0.8000	0.1429
2	0.0021	0.4489	0.8000	0.1429
3	0.0027	0.3470	0.8000	0.1429
4	0.0107	0.6102	0.8000	0.1429
5	0.0115	0.3020	0.6000	0.1429
6	0.0027	0.4450	0.8000	0.1429
7	0.0072	0.4897	0.6000	0.1429
8	0.0002	0.2449	0.8000	0.1429
9	0.0040	0.2328	1.0000	0.1429
10	0.2793	0.3265	0.8000	0.1429

3.3 Formulation of Export Guidelines for Neural Network Training
In this work, the two-layer feedforward network has been used for data classification, thus for training the network, the input and output data should be available. For the training of Feed Forward Neural Network, a set of guidelines was prepared after consulting

various academic experts and retail managers based on the importance of input criteria. This dataset consisting of 4 inputs (profit, demand, lead time and shelf-life) and output(category/group) was used for training the neural network All input variable values were categorized into A, B, and C groups. And normalization takes place in range 0 to 1 with the help of excel [14]. According to their Partial average scores, they assigned rank. In this worktop rank products (20%) has been assigned category A, middle-rank products (30%) assigned category B and remaining products (50%) assigned category C according to Pareto principle.

The Neural Network Toolbox (pattern recognition and classification app) of MATLAB can only recognize a target matrix in terms of 0s and 1s. So the form of the sample target matrix is shown as figure 4.

Class	Product 1	Product 2	Product 3
A	0	1	0
B	1	0	0
C	0	0	1

Fig. 4: Sample of the target matrix

According to table product, 1 belongs to class B, product 2 belongs to class A and product 3 belongs to class C.

These guidelines gave us initial datasets of input and output values for training the neural network for classification. The complete dataset of 220 products, for the train the network, consisting of normalized input values as well as their corresponding output obtained by following above guidelines have been given in Table 1 and table 2 for sample

Table 2: Target dataset to the train the network

S. no.	A	B	C	Category
1	0	1	0	B
2	0	1	0	B
3	0	1	0	B
4	1	0	0	A
5	0	0	1	C
6	0	1	0	B
7	0	0	1	C
8	0	0	1	C
9	0	1	0	B
10	1	0	0	A

3.4 Developing the Neural Network Classifier Model
The multi-layer feed forward neural network has been used here for classification of inventory products along with Scaled Conjugate Gradient for Fast Supervised Learning Neural Networks [15] as learning algorithm which is considered as the most efficient neural network for classification purpose.

Considering the continued nature of output in our case, sigmoid function in the hidden layer and Softmax function in the output layer has been used in this work. This model consisting two hidden layers with input and output layer these are known as input layer in which inputs are provided, two hidden layers for processing and approximating the relationship between input and output and finally, the output layer which gives output variables usually defined the feed forward neural network architecture as shown in figure 5.
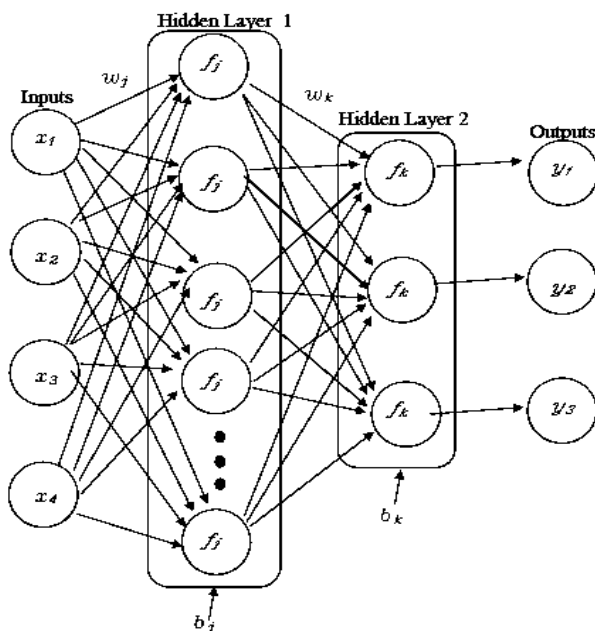
Fig. 5: Neural Network classifier model

3.5 Training and Validating and testing the neural network classifier model

Training is the learning process of any neural network by which input and target data are repeatedly presented to the network. This process is used the best set of weights for the network and approximate the relationship between inputs and targets, which allow the network to classify the input vectors with a satisfactory level of accuracy. For this work, all datasets were split into two groups namely a training group (220 products) and a test group (151 products). The feed-forward neural network was trained using the 220 products. The training itself consists of three phases namely training, testing and finally validation of network. Pattern Recognition and classification tool in MATLAB itself allocates 70% of the training dataset for training stage and 15% for testing and 15% validation. It was trained using four input parameters.

Its performance was analysed using cross entropy and confusion matrix. After the three training phases of neural network training are over, its accuracy is again validated by using targets. Its performance against them can give us a fair idea about the reliability of the network. And validate the network outputs with purposed targets which is prepared using guidelines. The theory behind this approach is to adjust the network weights in the direction of minimizing the error between desired and network outputs.

3.6 Testing of the trained neural network classifier model

This testing process is completed by two data sets first consisting of 80 products and the second consisting of 71 products. These datasets are tested in trained neural network and after testing considering the level of accuracy achieved in classification, we can say that a Neural Network based expert system has been developed which can easily be used for profit based inventory classification of any retail store's products.

4. SIMULATION AND RESULTS

4.1 Neural Network classifier model

In this work, 220 datasets of different products obtained by conducting a survey were used for training the network in which 70% were for training and remaining 30% (15% for each) were used for testing and validation. The development of this classifier model for multi-criteria inventory classification was carried out on neural network pattern recognition and classification app of MATLAB software.

4.1.1 Selection of Network wizard: For a selection of wizard for this work, open the ANN toolbox with command "start" in the command window and select Pattern Recognition and classification wizard (nprtool)

For the creation of the network, a two-layer feed-forward network, with sigmoid function in the hidden layer and softmax function in the output layer is used with scaled conjugate gradient backpropagation training algorithm and the performance of the network is evaluated using cross-entropy and confusion matrices.

4.1.2 Input and output Datasets: The input and target datasets will be imported into the network which has been already prepared in normalized form. For this work, an input dataset, 4x220 matrix, representing the 220 products with 4 criteria and in target dataset, 3x220 matrix, representing 220 products of 3 classes.

4.1.3 Setup the division of datasets: In training, validation and testing the 220 datasets randomly divided up to 70 % for training, 15% for validation and 15% for testing.

4.1.4 Network architecture: After defining the training, validation and testing datasets the number of hidden layers selected as 16 for this work by many trials.
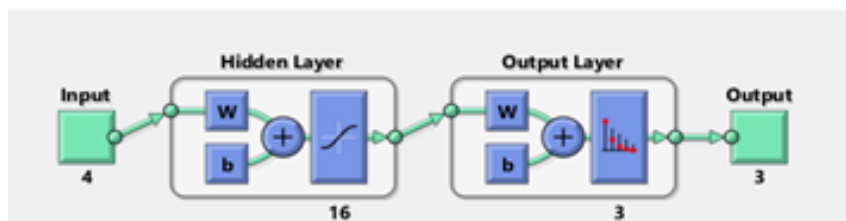
Fig. 6: Selection of neurons for training the network.

4.1.5 Train the network: For training, the network by default the scaled conjugate gradient backpropagation algorithm is used for the train the network. At this stage, the networking train again and again until the acceptable performance be archived and 100% performance was archived during training the network

4.1.6 Test the network to classify the inputs: After training the network, network has been checked according to plotting the performance curve, training stage, confusion matrix and ROC curve that the network is being acceptable or not if network is not benign acceptable than retrain the network until proper classification reached near about acceptable level and proceed further next step. In this work, 100% proper classification has been achieved as shown in figure 7.
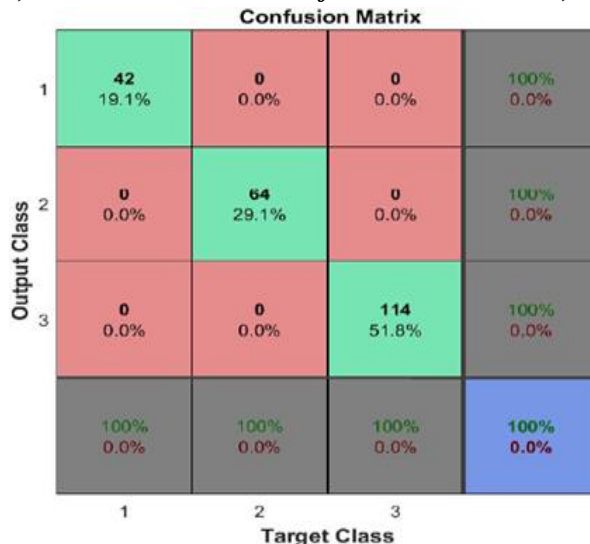
Fig. 7: Confusion matrix between target classes and output classes

The best validation performance of this network is 0.0077268 achieved at 69 epochs as shown in fig. 8. Which mean the validation performance reached a minimum.
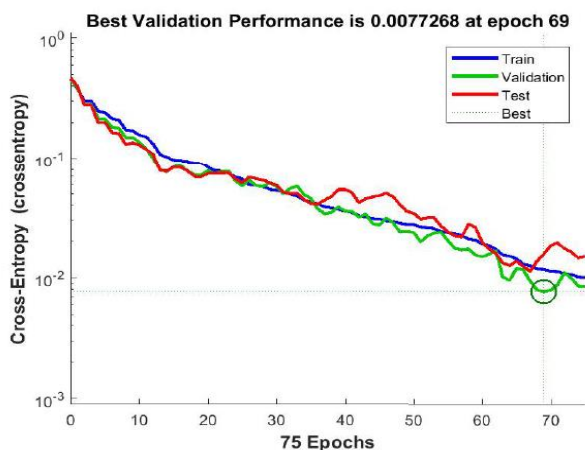
Fig. 8: Performance of network with Cross-Entropy

Figure 9 shows the confusion matrices for training, testing, and validation, and the three kinds of data combined. The outputs of the network are very accurate, as we can see that in the green squares, the high numbers of correct responses and in the red squares, the low numbers of incorrect responses and the overall accuracies illustrate in the lower right blue squares which have been 100%.

Fig. 9: Confusion matrixes of network

The ROC curve is a plot of the true positive rate (sensitivity) versus the false positive rate (1 - specificity) as the threshold is varied, the colored lines in each axis represent the Receiver Operating Characteristic curve. A perfect test, show points in the upper-left corner, with 100% sensitivity and 100% specificity. For this work, the network performs very well as shown in figure 10.
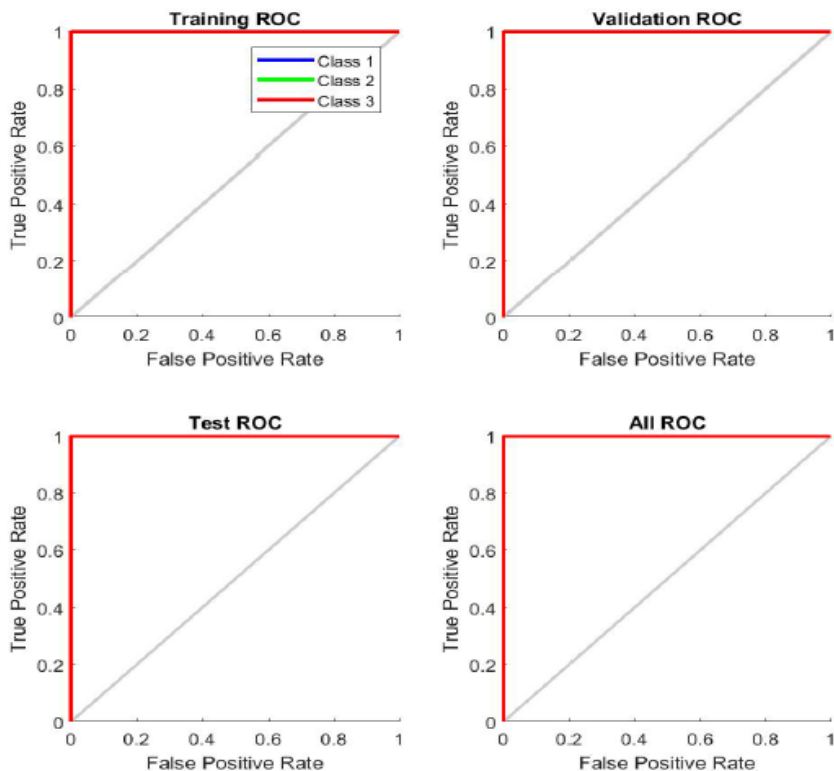
Fig. 10: Receiver operating characteristics curve of network

4.2 Testing of trained classifier model with input datasets

Testing of the trained network has been carried out by two samples of 80 and 71 products. These samples have only inputs and outputs obtained by the trained network so in this step test data has been importing in form of 0s and1s. The output has been obtaining in the form 0s and 1s. After testing the output data has been changed in vector form which are classes of products.

Now we have to identify the classes of the 80 and 71 new products. The training data matrix had each sample in a different column. So we also have to arrange the testing data of new products, with each sample in a different column.

Table 3: Input datasets for test sample 1

S. no.	Profit (Rs./Unit)	Demand (Units/week)	Lead Time (Days)	Shelf-Life (Days)
221	0.366	0.001	0	0.634
222	0.354	0.011	1	0.634
223	0.128	0.131	0.75	0.634
224	0.049	0.12	0.5	0.634
225	0.085	0.172	0.75	0.634
226	0.07	0.119	1	0.634
227	0.057	0.098	0.25	0.634
228	0.031	0.138	0	0.634
229	0.026	0.165	0.75	0.634
230	0.396	0.002	0.5	0.634
231	0.071	0.006	0.5	0.634
232	0.378	0.002	0.75	0.634
233	0.442	0.004	1	0.634
234	0.468	0.014	0.25	0.634
235	0.041	0.098	0	0.634
236	0.108	0.103	0.75	0.634
237	0.069	0.096	0.5	0.272
238	0.072	0.006	1	0.634
239	0.073	0.009	0.5	0.634
240	1	0	1	0.634
241	0.069	0.006	0.75	0.634
242	0.241	0.029	0.5	0.634

Table 4: Input datasets for test sample 2

S. no.	Profit (Rs./Unit)	Demand (Units/week)	Lead Time (Days)	Shelf-Life (Days)
301	0.06	0.07	0.25	0.63
302	0.26	0.10	0.00	0.63
303	0.14	0.51	0.00	0.00
304	0.06	0.36	0.75	0.00
305	0.06	1.00	0.50	0.00
306	0.33	0.21	0.75	0.00
307	0.09	0.63	1.00	0.44
308	0.08	0.50	0.25	0.44
309	0.08	0.26	0.00	0.63
310	0.33	0.38	0.75	0.63
311	0.31	0.45	0.50	0.63
312	0.35	0.02	0.75	0.63
313	0.13	0.20	1.00	0.63
314	0.06	0.65	1.00	0.63
315	0.26	0.19	0.75	0.44
316	0.29	0.57	0.75	0.44
317	0.25	0.26	0.75	0.44
318	0.05	0.20	0.75	1.00
319	0.10	0.39	0.50	1.00
320	0.09	0.21	0.50	0.25
321	0.50	0.80	0.75	0.25
322	1.00	0.39	0.50	0.25

243	0.068	0.001	0.75	0.634	323	0.06	0.04	0.00	0.25
244	0.331	0.016	1	0.634	324	0.08	0.41	0.25	0.25
245	0.128	0.06	0.75	0.634	325	0.00	0.24	0.00	0.44
246	0.673	0.003	0.75	0.634	326	0.37	0.11	0.25	0.44
247	0.712	0.006	0.75	0.634	327	0.24	0.58	0.75	0.44
248	0.114	0.001	0.75	0.634	328	0.14	0.50	0.75	0.44
249	0.364	0	0.5	0.634	329	0.05	0.32	0.75	0.44
250	0.362	0.007	0.75	0.634	330	0.03	0.66	0.00	0.44
251	0.067	0.004	0.75	0.634	331	0.04	0.23	0.25	0.44
252	0.072	0.003	0.75	0.634	332	0.01	0.52	0.50	0.25
253	0.357	0.003	1	0.634	333	0.02	0.20	0.50	0.63
254	0.357	0.009	0.25	0.634	334	0.11	0.52	0.75	0.63
255	0.165	0.116	1	0.634	335	0.12	0.35	0.75	0.63
256	0.07	0.021	0.75	0.997	336	0.04	0.20	0.75	0.63
257	0	0.21	0.75	0.634	337	0.04	0.39	0.25	0.63
258	0.584	0.01	0.5	0.634	338	0.09	0.25	0.00	0.63
259	0.07	0.006	0.75	0.634	339	0.21	0.49	0.75	0.63
260	0.067	0.019	0.75	0.997	340	0.11	0.65	0.75	0.63
261	0.065	0.006	1	0.997	341	0.03	0.70	0.50	0.25
262	0.049	0.292	1	0.997	342	0.07	0.43	0.75	0.25
263	0.067	0.017	0.75	0.634	343	0.10	0.30	0.50	0.44
264	0.067	0.009	0.75	0.634	344	0.17	0.28	0.25	0.63
265	0.409	0.09	0.75	0.272	345	0.27	0.01	0.00	0.81
266	0.017	0.006	0.5	0.272	346	0.11	0.00	0.25	0.63
267	0.026	0.123	0.5	0.634	347	0.06	0.00	0.75	0.25
268	0.546	0.158	0.75	0.634	348	0.04	0.71	0.50	0.25
269	0.07	0.006	1	0.634	349	0.01	0.25	0.75	0.25
270	0.069	0.009	1	0.634	350	0.05	0.40	0.00	0.25
271	0.071	0.16	0.75	0.634	351	0.05	0.20	0.50	0.38
272	0	0.155	0.75	0.634	352	0.45	0.35	0.25	0.38
273	0.158	0.182	0.75	0.634	353	0.05	0.36	0.75	0.44
274	0.097	0.176	0.75	0.634	354	0.07	0.35	0.75	0.44
275	0.038	0.191	0.75	0.634	355	0.01	0.43	0.00	0.25
276	0.035	0.105	0.5	0.634	356	0.61	0.10	0.50	0.25
277	0.042	0.1	0.75	0.634	357	0.04	0.52	0.75	0.06
278	0.073	0.002	1	0.634	358	0.02	0.32	0.25	0.06
279	0.07	0	0.25	0.634	359	0.04	0.49	0.25	0.25
280	0.251	0.226	1	0.091	360	0.38	0.39	0.00	0.25
281	0.148	0.202	0.75	0.091	361	0.54	0.24	0.00	0.25
282	0.057	0.054	0	0.091	362	0.41	0.24	0.75	0.44
283	0.012	0.194	0.75	0.091	363	0.18	0.52	0.50	0.44
284	0.147	0.151	0.25	0.091	364	0.59	0.38	0.75	0.44
285	0.073	1	0	0.091	365	0.22	0.70	0.25	0.44
286	0.015	0.262	1	0.091	366	0.22	0.53	0.25	0.44
287	0.043	0.198	0.75	0.091	367	0.08	0.47	0.00	0.25
288	0.039	0.096	0	0.091	368	0.38	0.04	0.75	0.25
289	0.148	0.181	0.25	0.181	369	0.04	0.33	0.50	0.25
290	0.072	0.105	0.75	0.272	370	0.77	0.25	0.75	0.25
291	0.003	0.315	0	0.634	371	0.06	0.08	0.75	0.25
292	0.049	0.103	0	0.091					
293	0.2	0.148	0	0.091					
294	0.031	0.118	0.75	0.272					
295	0.051	0.284	1	0.272					
296	0.027	0.257	0.75	0.091					
297	0.066	0.119	0.5	0.091					
298	0.098	0.007	0.5	0					
299	0.096	0.13	0.75	0					
300	0.114	0.134	0.75	0					

Now it is required to test the samples by the trained network it needs to write in the command window as:

testdata1result=net (testdata1) % for output.

testdata1resultind=ind2vec (testdata1result) % for convert the indices to vectors.

By this command, the network gives the outputs according to input datasets by the trained network. So below table show as the category of test datasets1 and 2.

S. No.	A	B	C	Category
221	0	1	0	B
222	1	0	0	A
223	0	1	0	B
224	0	0	1	C
225	0	1	0	B
226	0	1	0	B
227	0	0	1	C
228	0	0	1	C
229	0	1	0	B
230	0	1	0	B
231	0	0	1	C
232	1	0	0	A
233	1	0	0	A
234	0	1	0	B
235	0	0	1	C
236	0	1	0	B
237	0	0	1	C
238	0	1	0	B
239	0	0	1	C
240	1	0	0	A
241	0	0	1	C
242	0	0	1	C
243	0	0	1	C
244	1	0	0	A
245	0	1	0	B
246	1	0	0	A
247	1	0	0	A
248	0	0	1	C
249	0	0	1	C
250	1	0	0	A
251	0	0	1	C
252	0	0	1	C
253	1	0	0	A
254	0	1	0	B
255	1	0	0	A
256	0	1	0	B
257	0	1	0	B
258	0	1	0	B
259	0	0	1	C
260	0	1	0	B
261	1	0	0	A
262	1	0	0	A
263	0	0	1	C
264	0	0	1	C
265	0	1	0	B
266	0	0	1	C
267	0	0	1	C
268	1	0	0	A
269	0	1	0	B
270	0	1	0	B
271	0	1	0	B
272	0	1	0	B
273	0	1	0	B
274	0	1	0	B
275	0	1	0	B
276	0	0	1	C
277	0	1	0	B
278	0	1	0	B
279	0	0	1	C
280	1	0	0	A
281	0	0	1	C
282	0	0	1	C

Table 4: Outputs of test sample 1

S. No.	A	B	C	Category
301	0	0	1	C
302	0	1	0	B
303	0	0	1	C
304	0	1	0	B
305	1	0	0	A
306	0	1	0	B
307	1	0	0	A
308	0	0	1	C
309	0	0	1	C
310	1	0	0	A
311	1	0	0	A
312	1	0	0	A
313	1	0	0	A
314	1	0	0	A
315	0	1	0	B
316	1	0	0	A
317	0	1	0	B
318	1	0	0	A
319	1	0	0	A
320	0	0	1	C
321	1	0	0	A
322	1	0	0	A
323	0	0	1	C
324	0	0	1	C
325	0	0	1	C
326	0	1	0	B
327	1	0	0	A
328	1	0	0	A
329	0	1	0	B
330	0	0	1	C
331	0	0	1	C
332	0	0	1	C
333	0	0	1	C
334	1	0	0	A
335	1	0	0	A
336	0	1	0	B
337	0	0	1	C
338	0	0	1	C
339	1	0	0	A
340	1	0	0	A
341	0	1	0	B
342	0	1	0	B
343	0	0	1	C
344	0	0	1	C
345	0	1	0	B
346	0	0	1	C
347	0	0	1	C
348	0	1	0	B
349	0	0	1	C
350	0	0	1	C
351	0	0	1	C
352	0	0	1	C
353	0	1	0	B
354	0	1	0	B
355	0	0	1	C
356	0	1	0	B
357	0	1	0	B
358	0	0	1	C
359	0	0	1	C
360	0	1	0	B
361	0	1	0	B
362	1	0	0	A

Table 5: Outputs of test sample 2

283	0	0	1	C		363	0	1	0	B
284	0	0	1	C		364	1	0	0	A
285	0	0	1	C		365	0	0	1	C
286	0	1	0	B		366	0	0	1	C
287	0	0	1	C		367	0	0	1	C
288	0	0	1	C		368	0	1	0	B
289	0	0	1	C		369	0	0	1	C
290	0	0	1	C		370	1	0	0	A
291	0	0	1	C		371	0	0	1	C
292	0	0	1	C						
293	0	1	0	B						
294	0	0	1	C						
295	0	1	0	B						
296	0	0	1	C						
297	0	0	1	C						
298	0	0	1	C						
299	0	0	1	C						
300	0	0	1	C						

4.3 Results analysis

Result obtained from training datasets and testing dataset has been shown in the above section. The purpose of this network is to allow the network to approximate the relationship between the inputs and outputs with acceptable range. This network was trained again and again using different no. of hidden neurons until the acceptable performance of network was obtained. In this work, 100% performance was achieved during training the network again and again. The performance of the trained network can understand by confusion matrix and cross entropy so according to the confusion matrix and performance of network this model was considered as well-trained. For the consistency of the trained network was further checked by adapting new input data without target with four criteria. For this work, two new sample of datasets were given this trained network without their respective targets. The output obtained by the network was considered as categories of products and assigned the classes to respective products so we can classify the inventory items using this well-trained classifier model. So this network model now can be considered as the expert system for carrying out multi-criteria inventory classification on profit based.

5. CONCLUSION

Traditionally, inventory is classified in different groups according to dollar usage value. But this kind of classification considers some important multi-criterion which are profit based. So, an approach which considers profit per unit as a most important criterion for classification along with other criteria has been proposed in this work. As multi-criteria classification becomes very complex, artificial neural network, which is known for its capabilities as an efficient classifier, was used. With the proper training of the neural network, an expert system model was developed which can efficiently classify the inventory of any retail outlet according to the four most important criteria. The model was further used for the classification of inventory without target value. The results indicated that the ANN model has very high accuracy. As profit earning capability of an item was given more emphasis while deciding the importance of that item in the inventory store, this classification approach helps us in maximizing the profit. Stock-outs of high profit earning items can easily be avoided. This approach also considers other important criteria like the demand of the item, shelf life and lead time. With the level of accuracy achieved by the ANN model, the store manager can reliably perform the classification of a large number of items easily and quickly. Further research work is required to examine this network with large no. of datasets with considering more criteria.

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