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DESIGN AND DEVELOPMENT OF MATERIAL AND INFORMATION FLOW FOR SUPPLY CHAINS USING GENETIC CELLULAR NETWORKS

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ABSTRACT : In a recent paper by authors (Ziarati and Ucan, January 2001) a Back Propagation-Artificial Neural Network (BP-ANN) was adapted for predicting the required car parts quantities in a real and major auto parts supplier chain. It was argued that due to the learning ability of neural networks, their speed and capacity to handle large amount of data, they have a potential for predicting components requirements and establishing associated scheduling throughout a given supply chain system.

This paper should be considered a continuation of the first paper as the neural network approach introduced in this paper replaces the BP-ANN by a new method viz., Genetic Cellular Neural Network (GCNN). The latter approach requires by far less stability parameters and hence better suited to fast changing scenarios as in real supply chain applications.

The model has shown promising outcomes in learning and predicting material demand in a supply chain, with high degree of accuracy.

Keywords: *Genetic Cellular Neural Network, Supply Chain*

ÖZET: Son yıllarda, geri yayılım tekniğine dayanan yapay sinir ağı (Ziarati and Ucan, January 2001) modeli ile gerçek bir firmanın malzeme tedarik zincirinde geleceğe dönük malzeme talep miktarı tahmin edilebilmiştir. Yapay sinir ağlarının hızlı olması, büyük miktardaki verinin ele alınabilmesi, malzeme akış diagramlarında geleceğe yönelik tahminlerde potensiel bir model olmalarını sağlamaktadır.

Bu makale, (Ziarati and Ucan, January 2001) makalesinin geliştirilmiş biçimidir. Burada yapay sinir ağ (YSA) yapısı yerine Genetik Hücresel Yapay Sinir Ağ (HYSA) modeli konulmuştur. Söz konusu yaklaşım daha az parametre ile kestirim yapabilmekte ve dolayısıyla hızlı değişimli gerçek tedarik zincir problemlerine daha hızlı uyum sağlamaktadır.

Önerilen modelin, tedarik zinciri problemlerinde, gerek eğitim sürecinin kısaltılmasında gerekse malzeme istek kestirimde üstün başarım göstermesi beklenmektedir.

Anahtar Kelimeler : *Genetik Hücresel Yapay Sinir Ağ Yapıları, Tedarik Zincirleri*

NOTATIONS :

A: CNN templates
ANN: Artificial Neural Network
B: CNN template
BP: Back-Propagation
CNN: Cellular Neural Network
ERP: Enterprize Resource Planning
EOQ: Economic Order Quantities
GA: Genetic Algorithm
GCNN: Genetic Cellular Neural Network
I: Threshold
MRP : Material Required/Resource Planning
MxN: Matrix dimensions of A and B templates
P: Input matrix used for training process
P1: Logarithm function of P
PP: Input matrix for testing
r: CNN neighbourhood level
R: Random variable
T: Target matrix used for training process
T1: Logarithm function of T
TT: Target matrix for testing
U: Input matrix
X: State matrix
Y: Piece-wice linear function output of CNN

1. Introduction

In many supply chains irrespective of the methodology used to manufacture and/or distribute parts there is no unified and/or streamlined system for material and information flow up and down a supply chain or between supply chains themselves. While Material Required/Resource Planning (MRP) packages and their off-springs viz., Enterprize Resource Planning (ERP) system have played a major part; these systems have no systematic capacity for learning, and hence rely on either "rules of thumb" or human decisions which could be case-related or subjective at a very least, or erraneous at worst.

The concept of neural networks is not new, they have been used in many related applications (Wang, November 2000; Stockton and Quinn, 1993; Ucan et al, 2001), but prediction of the required number of components in a given supply chain is considered a new approach.

Prediction of components required and their flow through the chain irrespective of approach adopted should also enable production planning to be carried out and parts distributed to the right place at the right time. Demand prediction could also lead to the estimation of the pack sizes and delivery schedules. A learning model once fed with actual initial data, can only get better. The continuous nature of neural calculations when combined with use of actual data is considered a novel approach in prediction of component quantities and related production schedulings and parts delivery.

2. The Problem

Table 1 shows a list of 69 auto components flowing through a supply chain and forwarded to 6 retail units, denoted as A, B, C, D, E and F down stream, over a 3-week period. The number ordered by each retail unit and the pack sizes are evident for each component. For instance, 9^A means that the retail unit has ordered 9 components of the type shown. As elucidated, there are cases where a retail unit may have ordered the same components (with the same or different quantity) more than once during the period under consideration, viz 3-week in this case, we add all the orders as a total.

The quantities were ordered by using a MRP/ERP based system (Ziarati and Khataee, April 1994) as well as a number of empirical equations (rules of thumb).

The MRP/ERP system applied did not base its preditions on the past trends. The complexity of the Tables (ie. number of components involved, existing pack sizes, variation in demands by retail units, variation in time of orders and Economic Order Quantities (EOQs), etc, did not allow for a systematic evaluation of material and information flows through the supply chain. The information used by manufacturers in this case to interact with central and regional distribution centres, and the information used between the distribution units and retailers, were not unified and/or integrated through a single database. The knowledge obtained was not based on a meaningful learning mechanism of past dealings and activities.

3. The Solution

The intention here is not to compete with MRP/ERP systems currently used by commercial and industrial organisations. These systems have proven extremely useful (Ziarati, May 1994) in that, pay-off due to their introduction unlike other high-tech systems viz., CAD, CAM, robotics, etc, has been substantial. As reported in [6] the high pay-offs were due to the fact that MRP/ERP systems provide an opportunity for managers to know what is going on and hence able to co-ordinate activities within their organisation effectively and efficiently, for instance reduce stocks.

The intention here is to complement the existing ERP systems. The neural network offers a learning mechanism which could help to predict demand trends more accurately (in terms of material quantities, pack sizes, EOQs, etc.) with due consideration for spatial and temporal requirements. There is no reason as to why a neural network ERP should not be a way forward in the near future.
An explanation of the neural network approach adopted for this problem is given in the following section. Immediately after, an explanation is provided as to how data was computed and how output data was obtained.

4. Genetic Cellular Neural Networks

Cellular Neural Networks (CNN) were introduced by Chua and Yang (1988). A general CNN neighbourhood structure is shown in Figure 1. The CNN structure is well suited for the computation of tabulated data (Figures 1&2). The CNN normalised differential state-equation can be described by matrix-convolution operators as:

$$\frac{dX}{dt} = -X + A * Y + B * U + I \tag{1}$$

where U, X, Y are input, state and output of an M x N matrix, while I is an offset vector. The model used for the input-output relationship is given in Figure 3. The feedback and feed-forward connections are represented by matrix A and B.

The relationship between the state and output is non-linear as defined by the Equation below:

$$Y_{ij} = 0.5 * \left[|X_{ij} + 1| - |X_{ij} - 1| \right] \tag{2}$$

The characteristics of a CNN cell are governed by piece-wise variation as elucidated in Figure 4. The variation of the CNN output is governed by Equation 1. Therefore, iteration is stopped only when the derivative of the state variable (dX/dt) becomes zero, leading to an output value given by:

$$Y_{ij}^{\infty} = Y_{ij} \tag{3}$$

For the CNN to be stable, Aand B should be symmetrical and the centre element of A must be ≥ 1 for a 3 x 3 matrix. Figure 5 elucidates the propagation principle of a two-dimensional CNN.

4.1 Genetic Algorithm

GCNN is a CNN incorporating a Genetic Algorithm (GA). GA is a learning algorithm which abides by rules of the genetic science. The algorithm has been successfully applied in a number of cases such as image processing, geophysics, etc. (Ucan, 2001; Davies, 1991). It uses a binary coding system to search for optimum values of A, B and I.

The process of natural selection causes chromosomes (in this case, a given set of A, B and I matrix elements) to be continually reproduced and optimised. In addition to reproduction, mutations may cause the off-springs to be different from those of their biological parents, and crossing over processes create different chromosomes in off-springs by changing some parts of the parents' chromosomes. Like nature, genetic algorithm solves the problem of finding good chromosomes by a random manipulation of the chromosomes.

The underlying principles of GA were first published by Holland (1962). The mathematical framework was developed in the 1960s and was presented in his pioneering book (1975). In optimisation applications, they have been used in many diverse fields such as, function optimisation, image processing, travelling sales person problem, system identification and control and so forth. In machine learning, GA has been used to learn syntactically simple string IF-THEN rules in an arbitrary environment. A high-level description of GA as introduced by Davis in 1991 is given by [8]. Here, this high level presentation has been used in the prediction of components requirements in a supply chain as described below:

Step1: Initialise a population of chromosomes – set a random value to A, B & I.
Step2: Evaluate each chromosome – reproduce viz. assign new values to A, B & I.
Step3: Create new chromosomes by mating; apply mutation and recombination as the parent chromosomes mate – optimise values of A, B & I.
Step4: Delete members of the population to make room for new ones - destroy intermediate values.
Step5: Evaluate the new chromosomes and insert them into the population – update the optimised values.
Step6: If dX/dt = 0, then stop and return the best values of A, B and I matrix elements; otherwise, go to Step 3.

Step 1&2 Constructing initial population and extracting the CNN templates

A chromosome is constructed consisting of the first five elements of matrixes A and B respectively, and value of I making a total of 11 different values (see equations 4 and 9). The other elements in matrixes A and B respectively have the same values as the corresponding first five (see equation 9). A given element of matrix A, B and I value is represented by 7 decimal digits (i.e. -1.3125) hence as a 16 bit register (memory location) is too small to hold this number, 32 bit registers are required. As the total number of elements for a chromosome is 11, therefore a chromosome can be represented by 32x11= 352 bits (see equation 10). At the start the values for A, B and I are randomly constructed. In each chromosome the first 32 bits represent the first element (A1,1), and the second 32 bits of the chromosome represents the second element (A1,2) and so on. There are 11 different values in a given chromosome as elucidated below:

$$S = \lfloor A_{1,1}, A_{1,2}, A_{1,3}, A_{2,1}, A_{2,2}, B_{1,1}, B_{1,2}, B_{1,3}, B_{2,1}, B_{2,2}, I \rfloor \tag{4}$$

Steps 3 - 6 Optimising chromosome

The CNN works with the matrixes of A, B, I belonging to the first chromosome. After, the CNN output appears as stable, a function is used to obtain the target value. This function is called the Cost Function which enables the target value to be computed from the output values. This process is repeated for each set of matrixes belonging to each chromosome in the population. The Cost Function used in this study is given below:

$$\cos t(A,B,I) = \sqrt{\sum_{i=1}^{M} \sum_{j=1}^{N} \left(P_{i,j} - T_{i,j}\right)^2} \tag{5}$$

where $P_{i,j}$ and $T_{i,j}$ are the elements of Tables 2 and 3 respectively. The elements of Table 2 give the number of components ordered at any time by a dealer for each item for the first, second and third "3-week" period. Similarly Table 3 is composed of the values for the fourth, fifth and sixth "3-week" period used as a target matrix for training purposes. Having found the Cost Function, the Fitness Function for each chromosome is determined by the following equation:

$$\text{fitness}(A, B, I) = \frac{1}{1 + \cos t(A, B, I)} \tag{6}$$

The criterion to end iteration is defined as follows:

$$\min \text{cost}\ (A,B,I) < 0.01 \tag{7}$$

where min represents the minimum value of the cost function defined in Equation (5). If the minimum cost function value (or error) of the chromosome is smaller than iteration criterion (Equation 7), computation is concluded and the chromosome whose fitness value is the maximum in the population is selected. The matrixes which have been extracted from this selected chromosome are considered to be the optimum matrixes.

Creating the next population, the fitness value of the only chromosome is sorted by a descending order. All of the fitness values are normalised in relation to the sum of the fitness values of the population. A number (R) relating to the normalised values between 0 and 1 is generated leading to an optimised chromosome.

4.2 Application of GCNN in Demand Predication within a Given Supply Chain – an Example

This example is based on actual data obtained in a real supply chain. By using the data given in Tables 2-5, the following sections describe how the GCNN model works. First the neural model needs to be trained. The two datasets P and T as shown in Tables 2 and 3 are used for this purpose. The P dataset consists of the quantities ordered (69 types of parts) by the six retail units during first 3-week period. Similarly, T dataset includes quantities sold by the six retail units during the same period. Since the difference between maximum values and the minimum values of the dataset elements is large (viz., buying and selling some parts in 6s and 7s and some in 100s), the datasets have been transformed as follows:

$$P1 = \log(P + 1) \qquad\qquad T1 = \log(T + 1) \tag{8}$$

The elements of both datasets P1 and T1 are divided by their maximum value. The same process is applied to the test datasets PP and TT (Table 4 and 5).

In optimisation of A, B and I templates, GA is used. In GA, the chromosomes are deleted from the population after a given number of iteration (30 in this trials), and also if their fitness is below a certain threshold set by Equations 5 and 6. This procedure is known as reproduction process. Reproduction process does not generate new chromosomes. It selects the best chromosomes in the population and increases the number of the chromosomes whose fitness values are relatively greater than the others.

At the end of the training process and after 143 generation later the following matrixes were found:

$$A=\begin{bmatrix} -1.3125 & -4.1250 & -5.1875 \\ -6.3750 & 1.0000 & -6.3750 \\ -5.1875 & -4.1250 & -1.3125 \end{bmatrix}$$

$$B=\begin{bmatrix} -0.6875 & -0.1875 & -7.0000 \\ -6.0625 & 4.1875 & -6.0625 \\ -7.0000 & -0.1875 & -0.6875 \end{bmatrix}$$

$$I = 5.750 \qquad (9)$$

The best chromosome which holds the above values of A, B and I is given by:

S=[10000101111001100001000000000001110001000101101111001010101101001011001100101001001010000000101110110110101101100010101011110110010100101101100110010000100000100100011000010000110011111100101000110011100001010010101000000110010111001101001101011001001000000011010110101000010110111011000101011101000111101101001111101100011111100101000001010011000000010] (10)

Tables (2-5) are transferred to 2-D image processing form as in Figure (6-7), where the values of the dataset elements are shown by varying gray levels in the range of [0,1]. Thus we are able to apply our proposed GCNN approach to the considered supply chain. By using Equations 8-10, we can obtain GCNN output for training and testing as in shown in Figures 6 and 7. As a result, we can say that GCNN has promising applications in learning and predicting material demand in a supply chain.

5. Conclusions

This paper is an attempt to predict the optimum material and information flow for use by supply chains. A new stochastic algorithm, namely Genetic Cellular Neural Network (GCNN) is proposed. The training procedure is achieved by Genetic Algorithm (GA) which is based on a biological optimisation. Matrixes A and B respectively and the value of I are required for the CNN. Only 11 different matrix element values are necessary; hence computation is based on determining only 11 parameters as against 100s and sometimes 1000s parameters needed by other neural network algorisms. Such a limited and small number of parameter requirements make the neural iteration very short compared to other methods.

Application of the existing bitmap and vector graphic techniques (Figures 6 and 7), used in image processing, presented in this paper, should be considered a novel approach in training of the neural networks and their use in predicting material flow in a given supply chain. The bitmap concept has added a third dimension to the tabulated data and the application of vector graphics is expected to enhance the connectivity within the proposed neural network architecture.

The new approach has promising outcomes in learning and predicting material and also information flow in a supply chain as shown in Figures 6 and 7. It has a potential to become a prediction tool within the existing ERP suite of software or be used for the development of neural ERPs in the near future.

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ITEM	PACK QTY			Q	U	A	N	T	I	T	I	E	S
Service Kit	1	9A	2F	3B	2C	2B	2C	2F	2B		13E	2F	2C
Wiper Blade	1	10A											
Brake Pad-Front Set	1	12A	11A	5A	4B						13A		
Oil Filter Cannister	1	23A		22A	17F	22A							
W/Screen Wiper Blade	1	25A	12B	21A	5E	5F	11A	6B	6C		6F	22B	
Cam Plate	1	21A											
Hydraul Brake Fluid	1	12A	8E	13B	42A	9B	8C	18A	8F	9B	23B		
PAD	1	30A											
Service Kit	1	1B											
Drive Belt	1	11A											
Service Kit XJ8	1	4B	14A	3E	3F	3B	4C	3E	3B	3F	15A	4B	
Service Kit 32000 km	1	4F	2C	3C	2C	2D					3F	2D	
HSMO Fluid 500 ML	12	48A	12C								24C		
Flange Locking Nut	1	51A											
On Plug Ignition COI	1	42A	10F	30A	24E	36A	12B				42A		
Bracket Bumper Blade	1	13E	40B								26F		
Number Plate Fixings	25	300E	200E										
Undertray Assy	1	5A											
Wishbone Bush	1	13A											
Hexagon Head Screw	1	36A	36A										
Bulb HI S5W	1	13A											
Service Kit 1600 km	1	8B	4B	8B	3D	5B	1E				3F	6B	
Anti-Raid SP	4	16D											
Anti Roll Bar Bush	1	4A											
THREADED INSERT	1	81B											
Push-in Fastener	1	19B									30A		
P CLIP	1	17B											
Rokut Rivet	1	48B									23F		
Pop Rivet	1	9C											
Vee Mounting	1	3F											
Cylinder Heat Bolt	14	14A											
Ziw Bayonet Long Life	5	25A											
Stud-Exhaust Mifold	5	20A											
Spark Plug	6	24A	24A										
Service Kit	1	7B	4B										
Brake Cleaner	1	36A											
Service Kit	1	1D	1D										
Service Kit	1	1E											
Fir Treellip	1	16B											
Nut	1	14B											
Setscrew	6	36C											
Locking Bolt	5	30D											
Screw Rivet	5	40E									40E		
Joint Manifold	5	10F											
Bolt(Cylinder Bolt)	14	56A	28E										
Service Kit XJ8	1	1B											
Alienment Grommet	1	10F											
Locking Nut	1	10F											
Plug-Metal Seal 25 mm	1	10F											
30 mm	1	10F											
40 mm	1	10F											
Sealing Plug	1	11F											
Blind Rivet	1										17B		
Festoon Bulb Sw	1										24B		
21/5W Bayonet Long/L	5										15C		
Oval WASHER	1										18F		
Grommet	1										21A		
Battery-Romote CTL	2										14A		
Damper Bush	1										14A		
Brake Cool Duct	1										10A		
Alternative Drive Belt	1										13A		
SLPFLX BUSH	1										13A		
Bush Upper Wibone	1										19A		
Syud	1										65A		
CAM COVER SEAL KIT	1										7A		
Water By-pass Hose	1										15A		
Earth Lead	1										19A		
H4 60/55W Long Life	1										10B		
Service Kit XJ8	1										1B		

Table 1. Product descriptions and quantities demanded by the dealers

ITEM NO	First 3 weeks						Second 3 weeks						Third 3 three weeks					
	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F
1	9	7	6	0	13	6	11	12	10	0	15	11	11	7	10	0	15	5
2	10	0	0	0	0	0	12	0	0	0	0	0	6	0	0	0	0	0
3	41	4	0	0	0	0	44	5	0	0	0	0	40	4	0	0	0	0
4	67	0	0	0	0	17	63	0	0	0	0	16	64	0	0	0	0	17
5	57	40	6	0	5	17	57	42	8	0	6	14	46	38	6	0	8	5
6	21	0	0	0	0	0	22	0	0	0	0	0	21	0	0	0	0	0
7	72	54	8	0	8	8	71	60	10	0	9	9	90	56	8	0	8	10
8	30	0	0	0	0	0	32	0	0	0	0	0	27	0	0	0	0	0
9	0	1	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0
10	11	0	0	0	0	0	12	0	0	0	0	0	11	0	0	0	0	0
11	29	14	4	0	6	6	31	21	3	0	7	9	29	16	4	0	11	8
12	0	0	7	4	0	7	0	0	11	4	0	8	0	0	6	0	6	6
13	48	0	36	0	0	0	50	0	46	0	0	0	48	0	36	0	0	0
14	51	0	0	0	0	0	50	0	0	0	0	0	51	0	0	0	0	0
15	150	12	0	0	24	10	170	19	0	0	26	11	156	14	0	0	24	10
16	0	40	0	0	13	26	0	41	0	0	14	28	0	40	0	0	13	26
17	0	0	0	0	500	0	0	0	0	0	600	0	0	0	0	0	550	0
18	5	0	0	0	0	0	6	0	0	0	0	0	5	0	0	0	0	0
19	13	0	0	0	0	0	14	0	0	0	0	0	14	0	0	0	0	0
20	72	0	0	0	0	0	76	0	0	0	0	0	90	0	0	0	0	0
21	13	0	0	0	0	0	14	0	0	0	0	0	13	0	0	0	0	0
22	0	31	0	3	1	3	0	32	0	4	2	4	0	29	0	3	1	6
23	0	0	0	0	16	0	0	0	0	20	0	0	0	0	0	20	0	0
24	4	0	0	0	0	0	5	0	0	0	0	0	8	0	0	0	0	0
25	0	81	0	0	0	0	0	78	0	0	0	0	0	79	0	0	0	0
26	30	19	0	0	0	0	32	21	0	0	0	0	30	23	0	0	0	0
27	0	17	0	0	0	0	0	18	0	0	0	0	0	26	0	0	0	0
28	0	48	0	0	0	23	0	52	0	0	0	25	0	46	0	0	0	23
29	0	0	9	0	0	0	0	0	10	0	0	0	0	0	12	0	0	0
30	0	0	0	0	0	3	0	0	0	0	0	4	0	0	0	0	0	6
31	14	0	0	0	0	0	28	0	0	0	0	0	28	0	0	0	0	0
32	25	0	0	0	0	0	30	0	0	0	0	0	30	0	0	0	0	0
33	20	0	0	0	0	0	30	0	0	0	0	0	30	0	0	0	0	0
34	48	0	0	0	0	0	72	0	0	0	0	0	54	0	0	0	0	0
35	0	11	0	0	0	0	0	13	0	0	0	0	0	12	0	0	0	0
36	36	0	0	0	0	0	34	0	0	0	0	0	24	0	0	0	0	0
37	0	0	0	2	0	0	0	0	0	5	0	0	0	0	0	3	0	0
38	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	2	0
39	0	16	0	0	0	0	0	18	0	0	0	0	0	14	0	0	0	0
40	0	14	0	0	0	0	0	16	0	0	0	0	0	12	0	0	0	0
41	0	0	36	0	0	0	0	0	30	0	0	0	0	0	42	0	0	0
42	0	0	0	30	0	0	0	0	0	35	0	0	0	0	35	0	0	0
43	0	0	0	0	80	0	0	0	0	0	80	0	0	0	0	0	90	0
44	0	0	0	0	0	10	0	0	0	0	0	15	0	0	0	0	0	15
45	56	0	0	0	28	0	70	0	0	0	42	0	42	0	0	0	28	0
46	0	1	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0
47	0	0	0	0	0	10	0	0	0	0	0	12	0	0	0	0	0	11
48	0	0	0	0	0	10	0	0	0	0	0	12	0	0	0	0	0	12
49	0	0	0	0	0	10	0	0	0	0	0	9	0	0	0	0	0	14
50	0	0	0	0	0	10	0	0	0	0	0	10	0	0	0	0	0	8
51	0	0	0	0	0	10	0	0	0	0	0	11	0	0	0	0	0	8
52	0	0	0	0	0	11	0	0	0	0	0	12	0	0	0	0	0	8
53	0	17	0	0	0	0	0	18	0	0	0	0	0	16	0	0	0	0
54	0	24	0	0	0	0	0	22	0	0	0	0	0	28	0	0	0	0
55	0	0	15	0	0	0	0	0	20	0	0	0	0	0	20	0	0	0
56	0	0	0	0	0	18	0	0	0	0	0	20	0	0	0	0	0	22
57	21	0	0	0	0	0	19	0	0	0	0	0	22	0	0	0	0	0
58	14	0	0	0	0	0	16	0	0	0	0	0	28	0	0	0	0	0
59	14	0	0	0	0	0	15	0	0	0	0	0	12	0	0	0	0	0
60	10	0	0	0	0	0	12	0	0	0	0	0	8	0	0	0	0	0
61	13	0	0	0	0	0	15	0	0	0	0	0	16	0	0	0	0	0
62	13	0	0	0	0	0	16	0	0	0	0	0	16	0	0	0	0	0
63	19	0	0	0	0	0	21	0	0	0	0	0	17	0	0	0	0	0
64	65	0	0	0	0	0	71	0	0	0	0	0	52	0	0	0	0	0
65	7	0	0	0	0	0	8	0	0	0	0	0	11	0	0	0	0	0
66	15	0	0	0	0	0	13	0	0	0	0	0	17	0	0	0	0	0
67	19	0	0	0	0	0	17	0	0	0	0	0	21	0	0	0	0	0
68	0	10	0	0	0	0	0	9	0	0	0	0	0	8	0	0	0	0
69	0	1	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0

Table 2. Input table (P) for training

ITEM NO	Fourth 3 weeks						Fifth 3 weeks						Sixth 3 weeks					
	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F
1	11	8	8	0	14	8	9	8	8	0	18	0	11	8	7	0	21	0
2	12	0	0	0	0	0	12	0	0	0	0	0	10	0	0	0	0	0
3	35	4	0	0	0	0	42	6	0	0	0	0	45	4	0	0	0	0
4	81	0	0	0	0	17	81	0	0	0	0	17	70	0	0	0	0	17
5	80	40	6	0	5	13	58	38	6	0	5	10	60	40	6	0	5	11
6	21	0	0	0	0	0	21	0	0	0	0	0	24	0	0	0	0	0
7	77	55	11	0	8	6	64	53	5	0	8	8	86	45	8	0	8	8
8	30	0	0	0	0	0	32	0	0	0	0	0	30	0	0	0	0	0
9	0	1	0	0	0	0	0	3	0	0	0	0	0	2	0	0	0	0
10	11	0	0	0	0	0	15	0	0	0	0	0	12	0	0	0	0	0
11	29	10	7	0	6	6	29	14	4	0	6	3	30	15	4	0	6	0
12	0	0	8	3	0	7	0	0	10	4	0	7	0	0	7	4	0	8
13	48	0	24	0	0	0	36	0	36	0	0	0	48	0	36	0	0	0
14	51	0	0	0	0	0	51	0	0	0	0	0	51	0	0	0	0	0
15	147	16	0	0	15	10	110	12	0	0	24	10	150	6	0	0	24	10
16	0	40	0	0	13	26	0	40	0	0	13	26	0	40	0	0	13	26
17	0	0	0	0	600	0	0	0	0	0	550	0	0	0	0	0	500	0
18	5	0	0	0	0	0	5	0	0	0	0	0	5	0	0	0	0	0
19	13	0	0	0	0	0	13	0	0	0	0	0	13	0	0	0	0	0
20	80	0	0	0	0	0	67	0	0	0	0	0	72	0	0	0	0	0
21	13	0	0	0	0	0	13	0	0	0	0	0	13	0	0	0	0	0
22	0	32	0	3	2	3	0	30	0	3	1	5	0	27	0	3	5	3
23	0	0	0	0	16	0	0	0	0	12	0	0	0	0	0	16	0	0
24	6	0	0	0	0	0	4	0	0	0	0	0	4	0	0	0	0	0
25	0	73	0	0	0	0	0	84	0	0	0	0	0	81	0	0	0	0
26	30	19	0	0	0	0	32	21	0	0	0	0	30	19	0	0	0	0
27	0	18	0	0	0	0	0	18	0	0	0	0	0	17	0	0	0	0
28	0	48	0	0	0	23	0	48	0	0	0	23	0	48	0	0	0	23
29	0	0	12	0	0	0	0	0	10	0	0	0	0	0	9	0	0	0
30	0	0	0	0	0	6	0	0	0	0	0	6	0	0	0	0	0	3
31	28	0	0	0	0	0	28	0	0	0	0	0	14	0	0	0	0	0
32	15	0	0	0	0	0	30	0	0	0	0	0	25	0	0	0	0	0
33	20	0	0	0	0	0	15	0	0	0	0	0	20	0	0	0	0	0
34	42	0	0	0	0	0	54	0	0	0	0	0	48	0	0	0	0	0
35	0	19	0	0	0	0	0	12	0	0	0	0	0	11	0	0	0	0
36	36	0	0	0	0	0	36	0	0	0	0	0	36	0	0	0	0	0
37	0	0	0	3	0	0	0	0	0	3	0	0	0	0	0	2	0	0
38	0	0	0	0	2	0	0	0	0	0	3	0	0	0	0	0	1	0
39	0	20	0	0	0	0	0	14	0	0	0	0	0	16	0	0	0	0
40	0	16	0	0	0	0	0	12	0	0	0	0	0	14	0	0	0	0
41	0	0	42	0	0	0	0	0	42	0	0	0	0	0	36	0	0	0
42	0	0	0	35	0	0	0	0	0	35	0	0	0	0	30	0	0	0
43	0	0	0	0	80	0	0	0	0	0	90	0	0	0	0	0	80	0
44	0	0	0	0	0	15	0	0	0	0	0	15	0	0	0	0	0	10
45	42	0	0	0	14	0	42	0	0	0	14	0	56	0	0	0	28	0
46	0	3	0	0	0	0	0	4	0	0	0	0	0	1	0	0	0	0
47	0	0	0	0	0	12	0	0	0	0	0	12	0	0	0	0	0	10
48	0	0	0	0	0	12	0	0	0	0	0	8	0	0	0	0	0	10
49	0	0	0	0	0	14	0	0	0	0	0	7	0	0	0	0	0	10
50	0	0	0	0	0	8	0	0	0	0	0	11	0	0	0	0	0	10
51	0	0	0	0	0	9	0	0	0	0	0	12	0	0	0	0	0	10
52	0	0	0	0	0	13	0	0	0	0	0	14	0	0	0	0	0	11
53	0	21	0	0	0	0	0	13	0	0	0	0	0	17	0	0	0	0
54	0	26	0	0	0	0	0	18	0	0	0	0	0	24	0	0	0	0
55	0	0	20	0	0	0	0	0	25	0	0	0	0	0	10	0	0	0
56	0	0	0	0	0	24	0	0	0	0	0	12	0	0	0	0	0	18
57	22	0	0	0	0	0	22	0	0	0	0	0	21	0	0	0	0	0
58	18	0	0	0	0	0	12	0	0	0	0	0	14	0	0	0	0	0
59	8	0	0	0	0	0	16	0	0	0	0	0	14	0	0	0	0	0
60	8	0	0	0	0	0	11	0	0	0	0	0	10	0	0	0	0	0
61	16	0	0	0	0	0	12	0	0	0	0	0	13	0	0	0	0	0
62	14	0	0	0	0	0	12	0	0	0	0	0	13	0	0	0	0	0
63	21	0	0	0	0	0	22	0	0	0	0	0	19	0	0	0	0	0
64	65	0	0	0	0	0	60	0	0	0	0	0	65	0	0	0	0	0
65	14	0	0	0	0	0	8	0	0	0	0	0	7	0	0	0	0	0
66	16	0	0	0	0	0	14	0	0	0	0	0	15	0	0	0	0	0
67	18	0	0	0	0	0	21	0	0	0	0	0	12	0	0	0	0	0
68	0	12	0	0	0	0	0	11	0	0	0	0	0	10	0	0	0	0
69	0	4	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0

Table 3. Target table (T) for training

İTEM NO	First 3 weeks						Second 3 weeks						Third 3 weeks					
	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F
1	9	7	11	0	13	6	5	10	6	0	13	6	15	5	10	0	13	5
2	10	0	0	0	0	0	10	0	0	0	0	0	10	0	0	0	0	0
3	25	4	0	0	0	0	44	4	0	0	0	0	63	4	0	0	0	0
4	54	0	0	0	0	17	67	0	0	0	0	17	60	0	0	0	0	17
5	57	40	6	0	5	6	57	35	6	0	5	8	52	37	6	0	5	11
6	21	0	0	0	0	0	21	0	0	0	0	0	17	0	0	0	0	0
7	72	41	5	0	8	5	71	65	41	0	8	8	72	56	7	0	8	8
8	30	0	0	0	0	0	30	0	0	0	0	0	30	0	0	0	0	0
9	0	1	0	0	0	0	0	1	0	0	0	0	0	3	0	0	0	0
10	11	0	0	0	0	0	11	0	0	0	0	0	11	0	0	0	0	0
11	24	11	1	0	6	3	29	11	4	0	6	6	29	14	1	0	4	8
12	0	0	7	4	0	7	0	0	7	4	0	7	0	0	6	4	0	7
13	48	0	36	0	0	0	36	0	36	0	0	0	72	0	30	0	0	0
14	51	0	0	0	0	0	51	0	0	0	0	0	51	0	0	0	0	0
15	125	12	0	0	24	10	130	12	0	0	24	10	132	7	0	0	21	5
16	0	40	0	0	13	26	0	40	0	0	13	26	0	40	0	0	13	26
17	0	0	0	0	250	0	0	0	0	0	400	0	0	0	0	0	425	0
18	5	0	0	0	0	0	4	0	0	0	0	0	3	0	0	0	0	0
19	11	0	0	0	0	0	11	0	0	0	0	0	9	0	0	0	0	0
20	72	0	0	0	0	0	48	0	0	0	0	0	48	0	0	0	0	0
21	13	0	0	0	0	0	13	0	0	0	0	0	13	0	0	0	0	0
22	0	31	0	3	1	3	0	23	0	1	1	3	0	29	0	3	2	3
23	0	0	0	0	9	0	0	0	0	20	0	0	0	0	0	15	0	0
24	4	0	0	0	0	0	2	0	0	0	0	0	4	0	0	0	0	0
25	0	79	0	0	0	0	0	79	0	0	0	0	0	76	0	0	0	0
26	30	19	0	0	0	0	30	19	0	0	0	0	30	11	0	0	0	0
27	0	12	0	0	0	0	0	14	0	0	0	0	0	17	0	0	0	0
28	0	48	0	0	0	23	0	40	0	0	0	23	0	40	0	0	0	23
29	0	0	9	0	0	0	0	0	9	0	0	0	0	0	7	0	0	0
30	0	0	0	0	0	1	0	0	0	0	0	3	0	0	0	0	0	5
31	14	0	0	0	0	0	7	0	0	0	0	0	28	0	0	0	0	0
32	20	0	0	0	0	0	15	0	0	0	0	0	25	0	0	0	0	0
33	15	0	0	0	0	0	20	0	0	0	0	0	15	0	0	0	0	0
34	48	0	0	0	0	0	48	0	0	0	0	0	48	0	0	0	0	0
35	0	7	0	0	0	0	0	8	0	0	0	0	0	9	0	0	0	0
36	36	0	0	0	0	0	36	0	0	0	0	0	36	0	0	0	0	0
37	0	0	0	6	0	0	0	0	0	6	0	0	0	0	0	6	0	0
38	0	0	0	0	1	0	0	0	0	0	3	0	0	0	0	0	2	0
39	0	23	0	0	0	0	0	16	0	0	0	0	0	16	0	0	0	0
40	0	14	0	0	0	0	0	11	0	0	0	0	0	7	0	0	0	0
41	0	0	36	0	0	0	0	0	30	0	0	0	0	0	36	0	0	0
42	0	0	0	30	0	0	0	0	0	35	0	0	0	0	35	0	0	0
43	0	0	0	0	75	0	0	0	0	0	80	0	0	0	0	0	85	0
44	0	0	0	0	0	10	0	0	0	0	0	15	0	0	0	0	0	10
45	56	0	0	0	14	0	56	0	0	0	28	0	56	0	0	0	28	0
46	0	1	0	0	0	0	0	1	0	0	0	0	0	3	0	0	0	0
47	0	0	0	0	0	10	0	0	0	0	0	10	0	0	0	0	0	10
48	0	0	0	0	0	2	0	0	0	0	0	8	0	0	0	0	0	7
49	0	0	0	0	0	10	0	0	0	0	0	10	0	0	0	0	0	10
50	0	0	0	0	0	8	0	0	0	0	0	5	0	0	0	0	0	5
51	0	0	0	0	0	10	0	0	0	0	0	10	0	0	0	0	0	10
52	0	0	0	0	0	9	0	0	0	0	0	9	0	0	0	0	0	9
53	0	17	0	0	0	0	0	12	0	0	0	0	0	15	0	0	0	0
54	0	24	0	0	0	0	0	18	0	0	0	0	0	19	0	0	0	0
55	0	0	15	0	0	0	0	0	9	0	0	0	0	0	10	0	0	0
56	0	0	0	0	0	18	0	0	0	0	0	7	0	0	0	0	0	9
57	21	0	0	0	0	0	17	0	0	0	0	0	25	0	0	0	0	0
58	14	0	0	0	0	0	14	0	0	0	0	0	12	0	0	0	0	0
59	14	0	0	0	0	0	11	0	0	0	0	0	11	0	0	0	0	0
60	10	0	0	0	0	0	10	0	0	0	0	0	11	0	0	0	0	0
61	13	0	0	0	0	0	13	0	0	0	0	0	15	0	0	0	0	0
62	13	0	0	0	0	0	13	0	0	0	0	0	11	0	0	0	0	0
63	19	0	0	0	0	0	19	0	0	0	0	0	22	0	0	0	0	0
64	65	0	0	0	0	0	55	0	0	0	0	0	65	0	0	0	0	0
65	7	0	0	0	0	0	6	0	0	0	0	0	3	0	0	0	0	0
66	15	0	0	0	0	0	15	0	0	0	0	0	15	0	0	0	0	0
67	19	0	0	0	0	0	21	0	0	0	0	0	26	0	0	0	0	0
68	0	10	0	0	0	0	0	10	0	0	0	0	0	7	0	0	0	0
69	0	1	0	0	0	0	0	3	0	0	0	0	0	2	0	0	0	0

Table 4. Input table (PP) for testing

ITEM NO	First 3 weeks						Second 3 weeks						Third 3 weeks					
	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F
1	7	7	8	0	10	8	9	7	6	0	13	4	7	7	5	0	11	9
2	5	0	0	0	0	0	10	0	0	0	0	0	10	0	0	0	0	0
3	37	2	0	0	0	0	32	4	0	0	0	0	39	4	0	0	0	0
4	67	0	0	0	0	17	53	0	0	0	0	17	65	0	0	0	0	17
5	57	40	6	0	5	11	41	45	2	0	5	9	51	34	5	0	5	16
6	20	0	0	0	0	0	21	0	0	0	0	0	17	0	0	0	0	0
7	66	48	10	0	8	7	63	46	7	0	8	5	65	56	5	0	7	8
8	25	0	0	0	0	0	30	0	0	0	0	0	32	0	0	0	0	0
9	0	3	0	0	0	0	0	3	0	0	0	0	0	5	0	0	0	0
10	9	0	0	0	0	0	9	0	0	0	0	0	11	0	0	0	0	0
11	26	12	4	0	4	7	29	14	4	0	6	6	25	16	2	0	2	4
12	0	0	7	3	0	7	0	0	6	3	0	5	0	0	7	3	0	7
13	24	0	36	0	0	0	48	0	36	0	0	0	36	0	33	0	0	0
14	51	0	0	0	0	0	49	0	0	0	0	0	49	0	0	0	0	0
15	127	12	0	0	24	5	135	12	0	0	24	10	136	12	0	0	24	10
16	0	40	0	0	13	17	0	40	0	0	13	26	0	40	0	0	13	20
17	0	0	0	0	300	0	0	0	0	0	450	0	0	0	0	0	600	0
18	3	0	0	0	0	0	5	0	0	0	0	0	1	0	0	0	0	0
19	11	0	0	0	0	0	13	0	0	0	0	0	11	0	0	0	0	0
20	48	0	0	0	0	0	49	0	0	0	0	0	49	0	0	0	0	0
21	11	0	0	0	0	0	13	0	0	0	0	0	13	0	0	0	0	0
22	0	28	0	3	1	3	0	35	0	3	3	3	0	26	0	1	6	3
23	0	0	0	0	15	0	0	0	0	16	0	0	0	0	0	17	0	0
24	2	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0	0
25	0	76	0	0	0	0	0	75	0	0	0	0	0	76	0	0	0	0
26	27	18	0	0	0	0	27	21	0	0	0	0	25	17	0	0	0	0
27	0	23	0	0	0	0	0	15	0	0	0	0	0	15	0	0	0	0
28	0	42	0	0	0	23	0	41	0	0	0	20	0	41	0	0	0	23
29	0	0	7	0	0	0	0	0	7	0	0	0	0	0	7	0	0	0
30	0	0	0	0	0	1	0	0	0	0	0	5	0	0	0	0	0	1
31	28	0	0	0	0	0	11	0	0	0	0	0	14	0	0	0	0	0
32	20	0	0	0	0	0	29	0	0	0	0	0	15	0	0	0	0	0
33	15	0	0	0	0	0	21	0	0	0	0	0	15	0	0	0	0	0
34	48	0	0	0	0	0	36	0	0	0	0	0	66	0	0	0	0	0
35	0	8	0	0	0	0	0	8	0	0	0	0	0	10	0	0	0	0
36	31	0	0	0	0	0	31	0	0	0	0	0	35	0	0	0	0	0
37	0	0	0	3	0	0	0	0	0	2	0	0	0	0	0	1	0	0
38	0	0	0	0	3	0	0	0	0	0	1	0	0	0	0	0	2	0
39	0	17	0	0	0	0	0	15	0	0	0	0	0	16	0	0	0	0
40	0	11	0	0	0	0	0	12	0	0	0	0	0	12	0	0	0	0
41	0	0	30	0	0	0	0	0	31	0	0	0	0	0	42	0	0	0
42	0	0	0	35	0	0	0	0	0	30	0	0	0	0	25	0	0	0
43	0	0	0	0	75	0	0	0	0	0	68	0	0	0	0	0	95	0
44	0	0	0	0	0	15	0	0	0	0	0	9	0	0	0	0	0	10
45	42	0	0	0	14	0	70	0	0	0	9	0	28	0	0	0	14	0
46	0	3	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
47	0	0	0	0	0	5	0	0	0	0	0	9	0	0	0	0	0	10
48	0	0	0	0	0	10	0	0	0	0	0	9	0	0	0	0	0	10
49	0	0	0	0	0	7	0	0	0	0	0	9	0	0	0	0	0	10
50	0	0	0	0	0	8	0	0	0	0	0	7	0	0	0	0	0	10
51	0	0	0	0	0	8	0	0	0	0	0	15	0	0	0	0	0	10
52	0	0	0	0	0	9	0	0	0	0	0	10	0	0	0	0	0	11
53	0	21	0	0	0	0	0	15	0	0	0	0	0	18	0	0	0	0
54	0	28	0	0	0	0	0	20	0	0	0	0	0	29	0	0	0	0
55	0	0	10	0	0	0	0	0	10	0	0	0	0	0	12	0	0	0
56	0	0	0	0	0	19	0	0	0	0	0	17	0	0	0	0	0	16
57	20	0	0	0	0	0	17	0	0	0	0	0	20	0	0	0	0	0
58	12	0	0	0	0	0	16	0	0	0	0	0	19	0	0	0	0	0
59	12	0	0	0	0	0	11	0	0	0	0	0	9	0	0	0	0	0
60	11	0	0	0	0	0	9	0	0	0	0	0	5	0	0	0	0	0
61	9	0	0	0	0	0	9	0	0	0	0	0	11	0	0	0	0	0
62	10	0	0	0	0	0	11	0	0	0	0	0	11	0	0	0	0	0
63	17	0	0	0	0	0	26	0	0	0	0	0	16	0	0	0	0	0
64	60	0	0	0	0	0	70	0	0	0	0	0	71	0	0	0	0	0
65	5	0	0	0	0	0	8	0	0	0	0	0	8	0	0	0	0	0
66	13	0	0	0	0	0	10	0	0	0	0	0	12	0	0	0	0	0
67	17	0	0	0	0	0	10	0	0	0	0	0	17	0	0	0	0	0
68	0	8	0	0	0	0	0	8	0	0	0	0	0	8	0	0	0	0
69	0	3	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0

Table 5. Target table (TT) for testing

FIGURES:

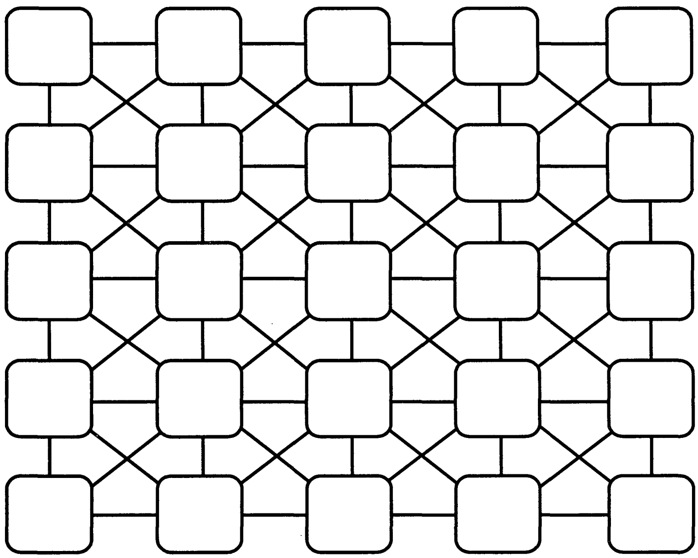
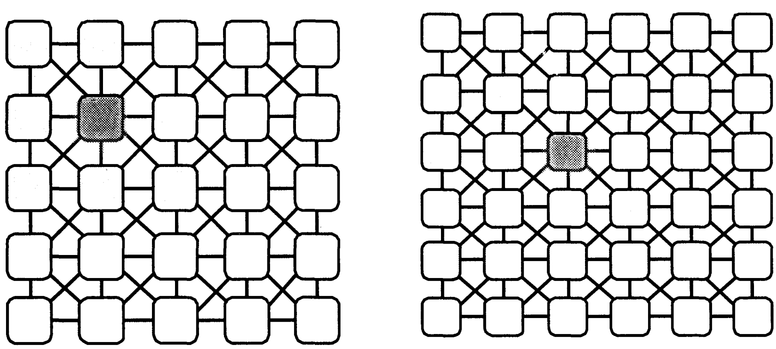


Figure 1. General CNN Neighbourhood Structure.



r=1 r=2

Figure 2. Representation of Neighbourhood Relation of CNN.

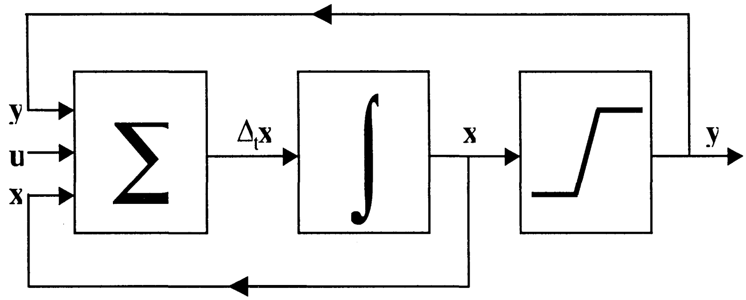


Figure 3. CNN model input-output relationship.

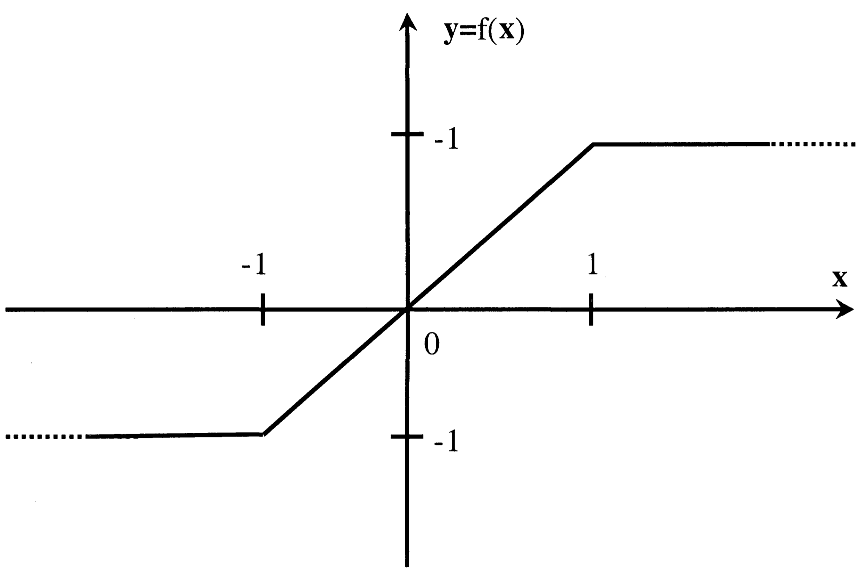


Figure 4. Piece-wise Linear Output Characteristics of CNN cell.

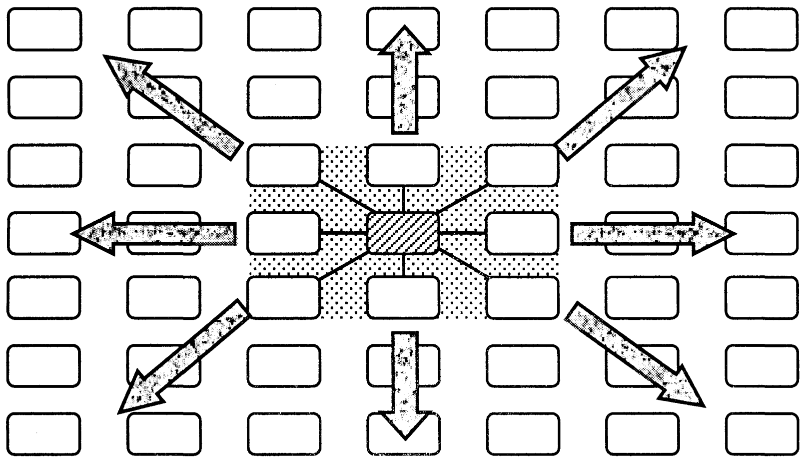
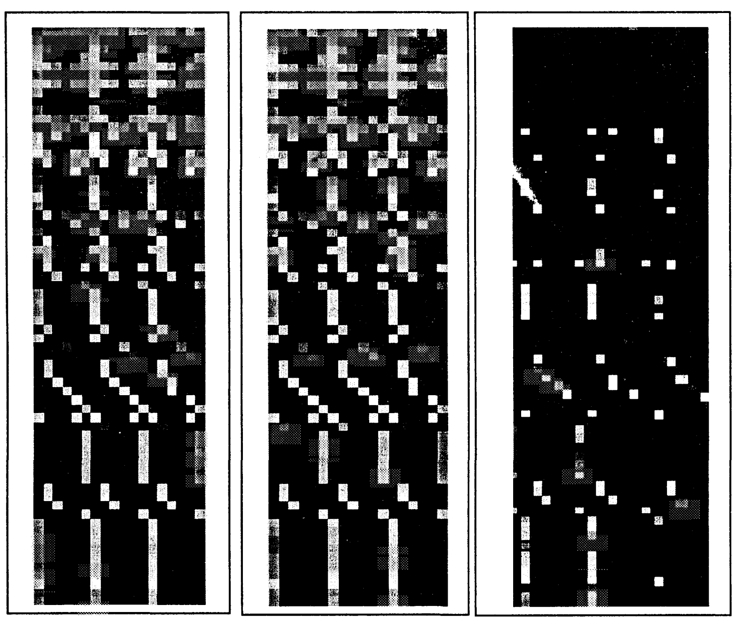


Figure 5. CNN propagation effect on 2-D images.

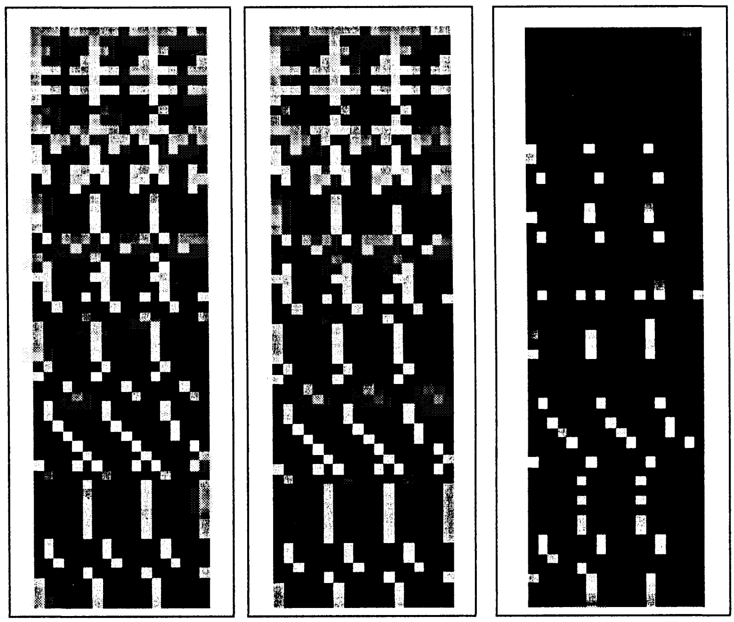


log (P+1)
INPUT
(a)

log (T+1)
DESIRED
(b)

log(Y+1)
GCNN OUTPUT
(c)

Figure 6 GCNN Application for training (a) 2-D image form of Table 1 (b) 2-D image form of Table 2 (c) GCNN output



(a)	(b)	(c)
log (PP+1) INPUT	log (TT+1) DESIRED OUTPUT	log (YY+1) GCNN

Figure 7. GCNN Application for testing (a) 2-D image form of Table 3 (b) 2-D image form of Table 4 (c) GCNN output