A Study on Functional Classification of the Municipalities in Bangladesh Using Artificial Neural Network

by

Annya Chanda Shimi

MASTER OF URBAN AND REGIONAL PLANNING

Department of Urban and Regional Planning

BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY

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The thesis titled, "**A STUDY ON FUNCTIONAL CLASSIFICATION OF THE MUNICIPALITIES IN BANGLADESH USING ARTIFICIAL NEURAL NETWORK,**" submitted by **Annya Chanda Shimi,** Roll No: **100715024P**, Session: **October 2007**, has been accepted as satisfactory in partial fulfillment of the requirements for the degree of **MASTER OF URBAN AND REGIONAL PLANNING** (by course and thesis) on **August 12, 2009**.

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Abstract

Bangladesh is often characterized by rapid urbanization and profound concentration of population in a few large cities. This leads to the growth of over-sized cities lacking adequate urban facilities. In order to manage the increasing demand for physical infrastructure and service facilities as well as to improve the living condition of people, it has become indispensable to develop secondary cities, Paurashavas (Municipalities), through visualization of their overall existing situations. At present, Paurashavas of Bangladesh are classified on the basis of the revenue those earn and the nature and extent of various municipal service facilities are not taken into account. It is a common experience in Bangladesh that many cities with large revenue earning provide inadequate and unsatisfactory service facilities. On the other hand, cities with less earning are seen to be quite satisfactory in such provisions. Obviously it is going to be like that when the factors revealing urban development are ignored in evaluation. In such a situation, it has become indispensable to devise and apply appropriate categorization tools that might reveal the real state of infrastructure and service facilities of the Paurashavas, such that appropriate planning and development measures can be taken.

In this research, an attempt has been made to understand the functional classification of Paurashava based on infrastructure and services by developing Artificial Neural Network (ANN) model Both supervised and unsupervised learning procedure of neural network has been employed to develop Artificial Neural Network (ANN) model for classification of the Paurashavas. Some basic functions amid compulsory and optional functions and non-agricultural characteristics of the Paurashava are considered to select variables for the research. A number of 125 Paurashavas has been selected for reclassification based on selected eighteen variables.

For all classes of Paurashavas, out of eighteen variables, mean values of most of the variables have been found larger and values of standard deviation have been found smaller in case of neural network classification than those in the existing classification. The neural network provides better classification of Paurashava in cases of mean value and value of standard deviation. Weighted average values of variables in case of the three classes of the existing classification vary abruptly and do not significantly express the hierarchy. But in neural network classification, the average values of variables in case of the three classes vary gradually and follow distinct hierarchy as well as distinct dissimilarity. Among selected Paurashavas for classification by using neural network algorithm, significant portion of Paurashavas fall under the lower hierarchy from the corresponding class. Finally, the developed artificial neural network model provides better classification of Paurashavas with respect to predicting correct classification, sensitivity and specificity. Value of sensitivity and specificity is fairly larger for this model.

By this research a classification of Paurashava marked by accelerating urbanization has been devised. Development of Artificial Neural Network (ANN) model for classification of Paurashavas will be more applicable for deriving logical development decisions to promote consolidated pattern of urban development. It is needless to mention that such an understanding is necessary for adopting planning approach, which would help in setting priorities in various fields of development, decentralize or relocate various service facilities and provide improved services at proper locations in the Paurashavas on the basis of their real need and potentialities, and thus to develop a strategy for balanced development.

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CHAPTER 1

INTRODUCTION

Chapter 1: Introduction

1.1 Background of the Study

Balanced and sustainable urban development is becoming a growing concern for cities of third world countries. Often in these countries, urbanization and its associated development is concentrated in a few large cities. There are relatively few secondary cities that are able to support non-agricultural economic activities which would diffuse the potential benefits of urbanization (Karan. 1994). Bangladesh is characterized by its rapid urbanization and profound concentration of population in a few large cities. The total urban population in Bangladesh increased to 29.26 million by 2001 (BBS. 2003). In 2001, nearly 50.46 percent of the total urban population is concentrated in Dhaka, Chittagong, Khulna and Rajshahi statistical metropolitan areas and Dhaka alone accounts for nearly 33.06 percent of the total urban population (Kakon, 2007). These statistics reflect that urbanization is not uniform throughout the country. In view of the problems in the over-sized large cities, a well-planned and balanced development of the secondary cities particularly Paurashavas or Municipalities may be considered as an excellent alternative.

According to the Paurashava Ordinance 1977, an urban area would be declared as a Paurashava if its three forth of the adult male population are engaged in non-agricultural occupations; population is not less than fifteen thousand and population density is not less than two thousand persons per square mile (LGED. 2001).

Paurashavas are established to render municipal services like provision of water supply and drainage, construction and maintenance of roads, provision and maintenance of street lighting, removal, collection and disposal of refuse, provision and maintenance of community facilities, maintenance of educational institutions, prevention of infectious diseases etc. to the urban dwellers within their jurisdiction under the legal framework of the Paurashava Ordinance 1977 (LGED. 2001). But most of the Paurashavas of Bangladesh lack proper drainage system. sufficient road network, adequate street lighting. regular garbage collection and adequate water supply (Ahmed, 2007). The high urbanization rate also made it difficult for the

Paurashavas to provide sufficient physical infrastructure and services for the urban dwellers and the deficiencies of municipal services ranged from severe to extreme (Haque et al , 2003).

At present, Paurashavas of Bangladesh are classified on the basis of revenue. The Government gazette notification of March, 1992 updated the East Pakistan Local Council Service Rules, 1968, classified Paurashavas into three categories on the basis of revenue. Class 'A' Paurashavas are those having average annual revenue income from their own sources of over Tk. 60, 00,000.00 in a three year period. Class 'B' Paurashavas are those having average annual revenue income between Tk. 25, 00,001.00 and Tk. 60, 00,000.00 in a three year period. Class 'C' Paurashavas are those having average annual revenue income between Tk. 10, 00,000.00 and Tk. 25, 00,000.00 (LGED, 2001).

The nature and extent of various municipal service facilities are not taken into account in this classification system. Even though the amount of revenue is quite important but it cannot be sole criteria for determining the category and hierarchy. In view of the constant failure of the municipal facilities in our secondary cities, there remains ample reason to believe that the present system of classification is erroneous. For example, under existing classification system Jamalpur Paurashava is a Class A Paurashava and has electricity coverage for 60% of population whereas Kalia and Durgapur both are Class C Paurashava and has electricity coverage of 71% and 23% respectively (NILG, 2002) This proved that based on the existing classification system any investment would favor Kalia over Durgapur though both are on same class: but investment need is much greater in Durgapur than Kalia. Similar conclusion could be drawn for Jamalpur. The classification based on revenue does not imply that municipal services would be superior quality in the Class A Paurashavas and inferior quality in the Class C Paurashavas. If a classification system is based on physical infrastructure and service facilities of the Paurashavas, this type of problems could overcome. This research focuses on classification system based on physical infrastructure and service provisions rather on revenue generation.

The efficient working of the Paurashavas is intricately related with the overall physical, economic and social conditions of the country In order to ensure efficient municipal services with varying nature. sound understanding and in depth knowledge of the concerned issues is needed. When such an exercise is to be carried out in a national scale and with limited resources, the prime necessity is to categorize those. In such a context, it has become indispensable to devise and apply appropriate categorization tools to manage the increasing demand for physical infrastructure and service facilities of the Paurashavas.

Cluster analysis by means of Artificial Neural Network (ANN) has been found well suited for classification in a wide variety of fields including business, biology, science, sociology, planning etc. It is expected that it could be an appropriate tool for classification of Paurashavas based on physical infrastructure and service facilities. Cluster analysis involves grouping of similar objects into distinct, mutually exclusive subsets referred to as clusters (Mangiameli et al., 1996).

Research on neural networks has been in existence for several decades. for the purpose of analyzing and classification (Cai, 2007; Liao & Wen, 2007; Kaski & Kohonen, 1996; Spielman & Thill, 2008). Artificial Neural Network (ANN), architecture inspired by the structure of the brain, is computational modeling tools that have been extensively used in many disciplines to model complex real-world problems (Liao & Wen, 2007). Neural nets has been applied to a wide variety of problems, such as storing and recalling data or patterns, classifying patterns, performing general mapping from input patterns to output patterns, grouping similar patterns, or finding solutions to constrained optimization problems (Fausett, 1994).

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are to complex to be noticed by either humans or other computer techniques (Khan et al., 2009). Developing Artificial Intelligence based classifiers is only part of a wider process of being more intelligent in how we go about building better spatial data classifications (Openshaw et al., 1995). In order to extract patterns or clusters of Paurashavas having similar characteristics from massively complex datasets describing multidimensional variables of physical infrastructure and service facilities of different Paurashavas, neural networks could be suitable methods. Precise determination of cluster memberships of Paurashavas is necessary to formulate appropriate policy and strategy for providing adequate municipal services and for infrastructure development.

Under this circumstance, an attempt has been made in this research to understand the functional classification of Paurashava based on infrastructure and services by developing Artificial Neural Network (ANN) model. It is needless to mention that such an understanding is necessary for adopting planning approach, which would help to decentralize service facilities and provide improved facilities in the Paurashavas on the basis of their potentialities and also to develop a strategy for balanced regional development.

1.2 Objectives of the Study

In order to determine the functional classification of Paurashavas, the following objectives are formulated:

- To classify Paurashavas (Municipalities) based on physical infrastructure and service facilities.
- To develop an Artificial Neural Network (ANN) model for Paurashavas.

1.3 Rationale of the Study

Several studies on Paurashavas have already been conducted but most of them are concerned with revenue and resource generation procedure of Paurashava according to the existing classification system. There are some other studies, which identified certain Paurashavas as study area and dealt with several aspects relevant to the study such as social, economical, educational, environmental aspects etc. Still there has been no study on the reclassification of Paurashavas on the basis of level of service facilities which are important determinants for Paurashava planning.

By this research a classification of Paurashava marked by accelerating urbanization will be devised. Due to lack of specific classification of Paurashavas based on service facilities, policy formulation and investment decision in Paurashavas is politically motivated. Development of Artificial Neural Network (ANN) model for classification of Paurashavas will be more applicable for deriving logical development decisions to promote consolidated pattern of urban development.

It is evident that the development of the secondary cities of the country would reduce the pressure of population on the few large cities. By deriving appropriate classification based on municipal services, potentialities of different Paurashavas can be identified which will be supportive to decentralize the municipal services and to provide improved facilities in Paurashava level. This understanding will help planners and policy makers for formulating planning and development policies in urban areas and accelerate the physical and social development by itself. Moreover, this research will help to assist various short and long term planning programs concerning Paurashavas.

1.4 Scope and Limitation of the Study

The research would focus on classification of Paurashavas based on physical infrastructure and service facilities. Indicators describing available municipal services, non agricultural characteristics and financial aspects of Paurashavas have been used to obtain applicable classification of Paurashavas that would be supportive to adopt any planning decisions. Among the clustering methods neural network based clustering methods provide more precise outcome. For this research, methods of neural network used for classification and clustering of data have been used to obtain accurate classification of Paurashavas.

Due to unavailability of relevant recent data, the research result may not depict the present or the most recent situation. All Paurashavas could not be included as data for all Paurashavas were not available. On the basis of functions performed by Paurashavas, indicators have been selected for reclassification of Paurashavas. Relative importance of these indicators on reclassification is not alike but there is no such standard or study regarding Paurashavas to determine the priority of the functions as well as to determine the weight of selected indicators. For this research, selected indicators are considered equally significant to determine classification of Paurashavas. It is anticipated that coverage of more Paurashavas and indicators would provide a more accurate picture.

1.5 Organization of the Study

This research comprises of six chapters. The first chapter describes the research background, rationality of the research, its objectives, scopes and limitations. The second chapter gives an idea of artificial neural network model and its application to the classification of Paurashavas. The third chapter consists of study design methodology from selection of variables to determination of the artificial neural network model with an overall description of the variables used in the research as well as sampling method of data. The fourth chapter provides explanation of infrastructure and service facility based classification of Paurashavas by means of artificial neural network algorithms and comparison of the new classification with the traditional classification to find out whether or how far these two vary. The fifth chapter illustrates the development procedure of artificial neural network model for classification of Paurashavas to address the application of it for class prediction of Paurashavas. The sixth chapter gives an overview of the research and concluding remarks of the research.

CHAPTER 2

THEORETICAL FRAMEWORK

Chapter 2: Theoretical Framework

2.1 Introduction

Artificial neural networks (ANNs) are non-linear mapping structures based on the function of the human brain. They have been shown to be universal and highly flexible function approximators for any data when the underlying data relationships are unknown. ANN becomes powerful tools for modeling. It has been used extensively over the past three decades for both classification and clustering. In order to develop the model for classification of Paurashavas, it is necessary to understand the concept of artificial neural networks as well as its application in classification and clustering.

2.2 Artificial Neural Networks (ANN)

2.2.1 Analogy with Human brain

The underlying motivation of Neural Network models is basically the human brain. The name is inspired from the "neuron", which is the computational unit of the human brain. A human brain has approximately 10^{11} neurons acting in parallel. The neurons are highly interconnected, with a typical neuron being connected to several thousand other neurons (Warneer & Misra, 1996). Figure 2.1 is the schematic diagram of a neuron, where the basic parts of a neuron and the passing of signal from neuron to neuron are shown.

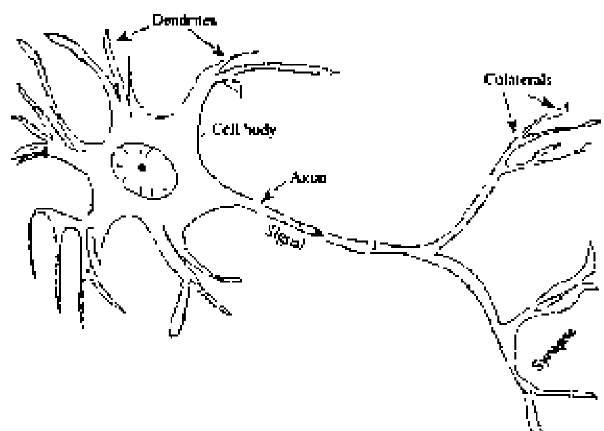


Figure 2.1: Schematic Diagram of Biological Neuron

The biological neuron is the basic building block of the nervous system. The biological neuron can simply be divided into three functional units- dedrites, cell body and axon. The cell body contains the main matters of the neuron, the dendrites receive signals from other neurons and pass them to cell body, and the axons, which branch into collaterals, receive signals from cell body and carry them away through synapse (A microscopic gap) (Basheer & Hajmeer, 2000). When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes.

The crude analogy between artificial neuron and biological neuron is that the connections between nodes represent the axons and dendrites. and connection weights represent the synapse, and the threshold approximates the activities in the soma (Basheer & Hajmeer, 2000). This analogy was first identified and modeled by McCulloch and Pitts in 1943 (Krose & Smagd, 1996; Zhang et al., 1998; Basheer & Hajmeer, 2000; Warneer & Misra, 1996), by the introduction of simplified neurons. Figure 2.2 shows these simplified neurons. These neurons were presented as models of biological neurons and as conceptual components for circuits that could perform computational tasks (Warneer & Misra, 1996).

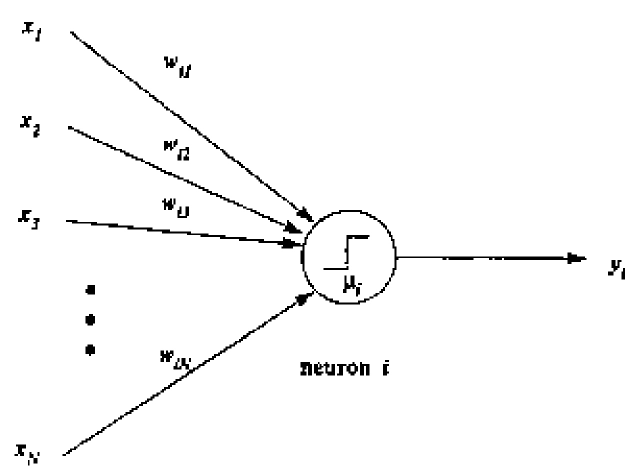


Figure 2.2: The McCulloch-Pitts Neuron

Here, $x_1, x_2, \ldots\ldots\ldots x_n$ are the inputs, $w_{i1}, w_{i2}, \ldots\ldots\ldots w_{in}$ are weightings of each input signal received by the neuron i, and y_i is the output signal. The neuron will be activated or fired if the sum of weighed inputs equals or exceeds a threshold value, μ_i.

Both biological and ANN learn by incrementally adjusting the magnitudes of the weights or synaptic strengths.

2.2.2 Definition

Though there are many definitions available for ANN, Fausett, (1994) and Haykin (1999) provide most widely used definition of ANN. Fausett, (1994) defines it as an information processing system that has certain performance characteristics in common with biological networks. Artificial neural networks have been developed as generalizations of mathematical models of human cognition or neural biology, based on the assumptions that,

- Information processing occurs at many simple elements called neurons.
- Signals are passed between neurons over connection links.
- Each connection link has an associated weight.
- Each neurons applies an activation function (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal (Fausett, 1994).

Haykin (1999) defines it as a massively parallel distributed processor made up of simple processing units, which has a neural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects.

1. Knowledge is acquired by the network from its environment through a learning process
2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

The attractiveness of ANNs comes from the remarkable information processing characteristics of the biological system such as nonlinearity, high parallelism, robustness, fault and failure tolerance, learning, ability to handle imprecise and fuzzy information and their capability to generalize (Jain et al., 1996).

Zhang et al., (1998) identified five features of ANNs that make them lucrative for modeling. Theses are:

- ANNs are data-driven self- adaptive methods. They learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe.
- It can generalize. After learning the data presented to them (sample), ANNs can often correctly infer an unseen part of a population even if the sample data contain noisy information.
- ANNs are universal function approximators. It has been shown that a network can approximate any continuous function to any desired accuracy ANNs have more general and flexible functional forms than the traditional statistical methods.
- Frequently, traditional statistical methods have limitations in estimating the underlying functions due to complexity of the real system. ANNs can be a good alternative method to identify this function.
- ANNs are nonlinear. Linear models are easy to understand and approximate, but they are totally inappropriate if the underlying mechanism is non linear. The real world systems are more often nonlinear than linear

2.2.3 Components of ANN

A neural network is characterized by-

- Its pattern of connection between the neurons (architecture).
- Its method of determining the weights on the connections (training or learning algorithm) and
- Its activation function (Fausett, 1994).

- ***Architecture***

Neurons and nodes are the points where signals are interconnected. There are some source nodes that supply the input signals to the neuron. Each node receives an input signal which is the "total" information from other nodes or external stimuli, processes it locally through an activation or transfer function and produces a transformed output signal to other nodes or external outputs. Each neuron is represented by a simple node called the computation node (Haykin, 1999). In each neuron or computation node, there are input signals coming from the input nodes, which are weighed and summed in the neuron, and an output value is supplied when the correct state of activation function is achieved.

- ***Learning algorithm***

ANNs are trained to produce the desired input-output relationships. During the training (learning) phase, examples are data are presented to the network and, using a learning algorithm, the parameters are tuned to adjust the network behavior. The learning algorithm employed to develop a network can be either "supervised", "unsupervised" or both.

- *Supervised learning or Associative learning* in which the network is trained by providing it with input and matching output patterns. These input-output pairs can be provided by the researcher, or by the system which contains the network (self-supervised) (Haykin, 1999). A neural net is said to learn supervised, if the desired output is already known. In supervised learning, training is accomplished by presenting a sequence of training vectors, or patterns, each with an associated target output vectors. The weights are then adjusted according to learning algorithm (Fausett, 1994).

- *Unsupervised learning or Self-organization* in which an (output) unit is trained to respond to clusters of pattern within the input. In this paradigm the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather the system must develop its own representation of the input stimuli. Neural nets that learn unsupervised have no such target outputs. Unsupervised learning or self-organizing neural nets group similar input vectors together without the use of training data to specify what a typical member of each group looks like or to which group each vector belongs. A sequence of input vectors is provided, but target vectors are not specified. The net modifies the weights so that the most similar input vectors are assigned to the same output (or cluster) unit (Fausett, 1994).

- ***Activation function***

The activation function is also called the transfer function. It determines the relationship between inputs and outputs of a node and a network. In general, the activation function introduces a degree of nonlinearity that is valuable for most ANN applications. In practice, only a small number of activation functions (bounded, monotonically, increasing, and differentiable) are used. These include:

1. The sigmoid (logistic) function:

   $f(x) = (1 + \exp(-x))^{-1}$

2. The hyperbolic tangent (tanh) function:

   $f(x) = (\exp(x) - \exp(-x))/(\exp(x) + \exp(-x))$

3. The sine or cosine function:

   $f(x) = \sin(x)$ or $f(x) = \cos(x)$

4. The linear function:

   $f(x) = x$

Among them, the sigmoid (logistic) function is the most popular choice (Zhang et al., 1998; Almeida, 2002).

2.2.4 Problems for ANN

Generally, ANNs are more robust and often outperform other computational tools in solving a variety of problems from seven categories- pattern classification, clustering, function approximation (modeling), forecasting, optimization, association, control (Basheer & Hajmeer, 2000). In this research pattern classification and clustering has been used to classify Paurashavas of Bangladesh according to the services provided by the Paurashava authorities.

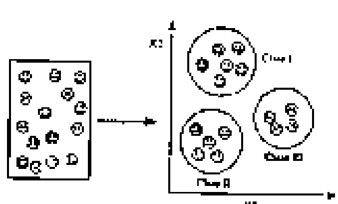
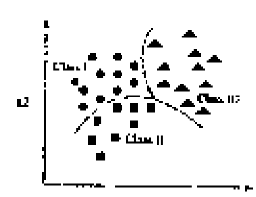
- ***Pattern classification***

Pattern classification deals with assigning an unknown input pattern, using supervised learning, to one of several prespecified classes based on one or more properties that characterize a given class, as shown in Table 2.1 (Basheer & Hajmeer, 2000). Unlike discriminant analysis in statistics, ANNs do not require the linearity assumption and can be applied to nonlinearly separable classes (Garth et al., 1996).

- ***Clustering***

Clustering is performed via unsupervised learning in which the clusters (classes) are formed by exploring the similarities or dissimilarities between the input patterns based on their inter-correlations (Table 2.1). The network assigns 'similar' patterns to the same cluster (Basheer & Hajmeer, 2000).

Table 2.1: Clustering and Pattern Classification

Clustering (unsupervised learning)	**Pattern Classification (class prediction, supervised learning)**
• Classes are unknown a priori. • Goal is to discover these classes from the data. 	• Classes are predefined. • Goal is to understand the basis for classification from a set of labeled objects and build a predictor for future unlabeled observations. 

Source: Basheer & Hajmeer, 2000

2.3 Artificial Neural Network Models

Many different ANN models have been proposed since 1980s. A vast number of networks, new or modifications of existing ones, are being constantly developed. Simpson (1990) listed 26 different types of ANNs, and Maren (1991) listed 48. Pham (1994) estimated that over 50 different ANN types exist. Well-known examples of ANNs used for clustering include Kohonen's learning vector quantization (LVQ) and self-organizing map (SOM) (Kohonen 1989), and adaptive resonance theory models (Carpenter and Grossberg 1990) and classification include Multi-layer perceptrons (MLP) or feed forward-back propagation networks (Basheer & Hajmeer, 2000)

Some applications may be solved using different ANN types, whereas others may only be solved via a specific ANN type. Some networks are more proficient in solving perceptual problems, while others are more suitable for data modeling and function approximation. The most influential ANN models are -

- Multi-Layer Perceptrons (MLP) or Feed Forward-Back Propagation Networks
- Hopfield Networks
- Kohonen's Self-organizing Networks (Zhang et al, 1998)

Kohonen's Self-organizing and Feed Forward-Back Propagation neural networks have been used for modeling in this research.

2.3.1 Self-organizing Neural Networks

The traditional multivariate statistical methods, like cluster analysis and ordination, are difficult to interpret and cannot well present the information of very large data set. Self-organizing neural network, Self-organizing Map (SOM), is a novel approach for the visualization of high-dimensional data (Varbiro, et al, 2007). SOM converts complex statistical relationships between datasets into simple geometric relationships on a low dimensional display. Thus it compresses information while preserving the most important topological and metric relationship of the primary data (Kohonen, 2001). The main advantages of the SOM are better data visualization and noise reduction (Vesanto and Alhoniemi, 2000).

For many decades, statisticians have used discriminant analysis and regression to model the patterns within data when there are labelled training data (with inputs and known outputs) available, and clustering techniques when no such data are available. These techniques find analogies in neural networks, where Multi Layer Feed Forward Networks are used with backpropagation when training data are available, and self-organizing neural networks are used as a clustering technique when no training data are available. Clustering has always been used to group the data based upon the natural structure of the data. The objective of an appropriate clustering algorithm is that the degree of similarity of patterns within a cluster is maximized, while the similarity these patterns have with patterns belonging to different clusters is minimized (Smith and Gupta, 2000)

Often patterns in a high-dimensional input space have a very complicated structure, but this structure is made more transparent and simple when they are clustered in a one, two or three dimensional feature space. Kohonen (1982, 1989) developed self-organizing map (SOM) as a way of automatically detecting strong features in large data sets. SOM finds a mapping from the high-dimensional input space to low-dimensional feature space, so the clusters that form become visible in this reduced dimensionality.

Mangiameli et al., 1996 compared self-organizing neural network and several hierarchical clustering methods, and found self-organizing neural network superior to hierarchical clustering in both robustness and accuracy. Identifying cluster membership in messy empirical data is a difficult problem that is confounded by data imperfections such as dispersion, outliers, irrelevant information, and nonuniform cluster densities. But self-organizing neural network is more accurate at assigning data observations to clusters for the "messy data" conditions that are typical of empirical field studies.

The SOM involves adapting the weights to reflect learning but the learning is unsupervised since the desired network outputs are unknown. In the SOM, input vectors are connected to an array of neurons, usually one-dimensional (a row) or two-dimensional (a lattice). Figure 2.3 shows this architecture for input and a square array of output neurons.

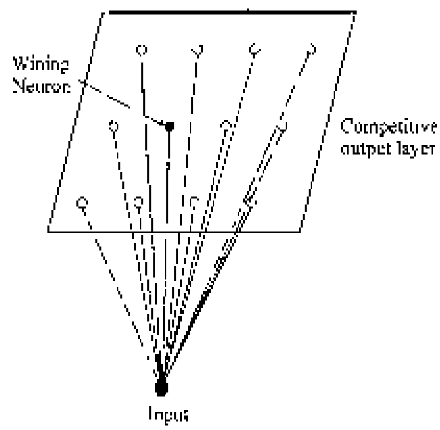


Figure 2.3: Architecture of SOM

When an input pattern is presented to the SOM, certain regions of the array will become active. and the weights connecting the inputs to those regions will be strengthened. Once learning is complete, similar inputs will result in the same region of the array becoming active or firing. If a neuron fires, it is likely that its neighbors will also fire concerning the physical location of the neurons. Kohonen's feature maps are motivated by the self-organizing behavior of the human brain (Kohonen, 1982). This idea has more biological justification than the other neural models, since the human brain involves large regions of neurons operating in a centralized and localized manner to achieve tasks. In the human brain, as in the SOM, there is usually a clear "winning neuron" which fires the most upon receiving an input signal, but the surrounding neurons also get affected by this, firing a little, and the entire region becomes active.

In order to replicate the response of the human brain in the SOM, the learning process is modified so that the winning neuron (defined as the neuron whose weights are most similar to the input pattern) receives the most learning, but the weights of neurons in the neighborhood of the winning neuron are also strengthened, although not as much. It is appropriate at this point to define the concept of a neighborhood in relation to the architecture of the SOM. For a linear array of neurons, the neighbors are simply the neurons to the left and right of the winner. This is called a neighborhood size of one. To achieve the effect of an active region of neurons, larger neighborhood sizes are considered, as shown in Figure 2.4 for rectangular array of neurons with a hexagonal neighborhood structure where m is the winning neuron and $N_m(t)$ is the neighborhood size.

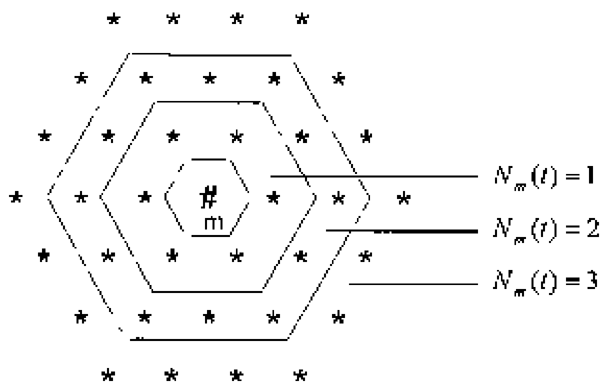


Figure 2.4: Neighborhood size for a Rectangular array of Neurons

Initially the neighborhood size around a winning neuron is allowed to be quite large to encourage the regional response to inputs. but as the learning proceeds, the neighborhood size is slowly decreased so that the response of the network becomes more localized. The localized response, which is needed to help clearly differentiate distinct input parterns, is also encouraged by varying the amount of learning received by each neuron within the winning neighborhood. The winning neuron receives the most learning at any stage; with neighbors receiving less the further away they are from the winning neuron.

- ***Stepwise Learning Algorithm of Self-organizing Neural network***

The learning algorithm for the Self-organizing neural networks follows the basic steps of presenting input patterns, calculating neuron outputs, and updating weights. The differences lie in the method used to calculate the neuron output (this time based on the similarity between the weights and the input). and the concept of a neighborhood of weight updates. The parameters of the algorithm are:

- A continuous input space of activation patterns that are generated in accordance with a certain probability distribution.
- A topology of the network in the form of lattice of neurons, which defines a discrete output space

- A time-varying neighborhood function c that is defined around a winning neuron m.
- A learning-rate parameter $\alpha(t)$ that starts at an initial value α_0 and then decreases gradually with time, but never goes to zero.

For good statistical accuracy, $\alpha(t)$ should be maintained at a small value (0.01 or less) during the convergence for a fairly long period of time, which is typically thousands of iterations. As for the neighborhood function, it should contain only the nearest neighbors of the winning neuron at the start of the convergence phase, and may eventually shrink to one or zero neighboring neurons.

The steps of the algorithm are as follows:

Step 1: Initialise

- weights (w) to small random values.
- neighborhood size $N_m(0)$ to be large.
- learning-rate parameter functions $\alpha(t)$ and $\sigma^2(t)$ to be between 0 to 1.

Step 2: Present an input pattern x through the input layer and calculate the closeness (distance) of this input to the weights of each neuron j :

$$d_j = \|x - w_j\| = \sqrt{\sum_{i=1}^{n}\left(x_i - w_{ij}\right)^2}$$

Step 3: Select the neuron with minimum distance as the winner m.

Step 4: Update the weights connecting the input layer to the winning neuron and its neighbouring neurons according to the learning rule

$$w_{ij}(t+1) = w_{ij}(t) + c\left[x_i - w_{ij}(t)\right]$$

where $c = \alpha(t)\exp\left(-\|r_i - r_m\|/\sigma^2(t)\right)$ for all neurons j in $N_m(t)$ and $r_i - r_m$ is the is the physical distance (number of neurons) between neuron i and the winning neuron m. The two functions $\alpha(t)$ and $\sigma^2(t)$ are used to control the amount of learning each neuron receives in relation to the winning neuron. These functions can be slowly decreased over time. The amount of learning is greatest at the winning neuron (where $i = m$ and $r_i = r_m$) and decreases the further way a neuron is form the winning neuron, as a result of the exponential function. Neurons outside the neighborhood of the winning neuron receive no learning.

Step 5: Continue from STEP 2 for many epochs; then decrease neighborhood size, $\alpha(t)$ and $\sigma^2(t)$:

Repeat until weights have stabilized

(Kohonen, 1988; Fausett, 1994; Haykin, 1999; Smith and Gupta, 2000)

2.3.2 Feed Forward-Back Propagation Neural Networks

Feed forward-back propagation Networks are also known as Multi Layer Perceptron (MLP) models or Multi Layer Feed Forward (MLFF) Networks and the most widely used type of networks and are considered the workhorse of ANNs (Rumelhart et al., 1986). These networks are appropriate for solving problems that involve learning the relationships between a set of inputs and known outputs.

Feed forward-back propagation networks consists of (i) an input layer with nodes representing input variables to the problem, (ii) an output layer with nodes representing the dependent variables (i.e., what is being modeled), and (iii) one or more hidden layers containing nodes to help capture the nonlinearity in the data. It is a supervised technique in the sense that it requires a set of training data in order to learn the relationships (Basheer & Hajmeer, 2000).

The term back propagation refers to the way the error computed at the output side is propagated backward from the output layer, to the hidden layer, and finally to the input layer. In this network, the data are fed forward into the network without feedback (i.e., all links are unidirectional and there are no same layer neuron-to-neuron connections). The neurons in the network can be fully or partially interconnected (Basheer & Hajmeer, 2000). Figure 2.5 shows the schematic view of such a network, where X values indicate inputs and Y indicates output values.

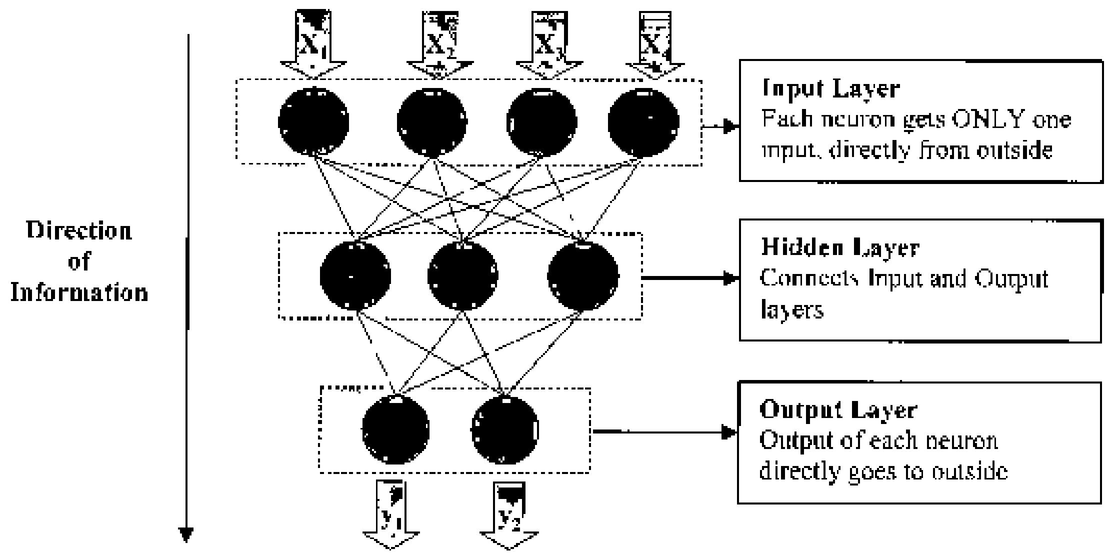


Figure 2.5: Schematic view of a Feed forward-Back propagation Network

The hidden layer(s) contain two processes: the weight summation functions and the activation function. Both of these functions relate the values from the input data to the output measures. The weighted summation function typically used in a feed forward-back propagation network model is:

$$Y_j = \sum_{j}^{n} X_i W_{ij}$$

Where X_i is the input values and W_{ij} is the weights assigned to the input values for each of the j hidden layer nodes. An activation function then relates the summation value (s) of the hidden layer(s) to the output value(s), Y_j. The sigmoid transformation function is preferred due to its non-linearity, continuity, monotonicity, and continual differentiability properties (Borst, 1992; Trippi and Turban, 1993)

In most research, the initial neural network model is created utilizing a training set of input and output data. The most common form of neural network systems are termed "feed forward" networks and begin with a default of randomly determined weights for each of the nodes in the hidden layers. At each hidden layer, the information is transformed by a nonlinear activation function to produce an output measure. The model then compares the model's output to the actual output for the discrepancy. If a discrepancy exists, the model works backwards from the output layer back through the hidden layer nodes, adjusting the weights so as to reduce the prediction error. With each ordered pair of input measures and output responses from the training set, the neural network repeats these steps until the overall prediction is minimized. A trained neural network model can be tested for accuracy by predicting responses from new input measures.

- ***Stepwise learning algorithm of feed forward back propagation neural network***

In summation, the back propagation algorithm can be expressed in terms of the following steps:

- Start with a random set of weights.
- Feed forward the first observation through the net

  $X_1 \rightarrow$ Network $\rightarrow V_1$; Error = $(Y_1 - V_1)$ where Y_1 is the actual output
- Adjust the weights so that this error is reduced (network fits the first observation well)
- Feed forward the second observation. Adjust weights to fit the second observation well.
- Keep repeating till the last observation is reached.
- This finishes one cycle (epoch) through the data.
- Perform many such training cycles till the overall prediction error E is small.

$E = \sum (Y_i - V_i)^2$, where Y_i is the actual value and V_i is the prediction value of i th observation.

(Fausett, 1994; Haykin, 1999; Smith and Gupta, 2000)

- ***Weight adjustment formula***

The formula for total prediction error, $EW = \sum [Y_i - V_i(\underline{W})]^2$

Where V_i, the prediction for ith observation is a function of the network weights vector $\underline{W} = (W_1, W_2, \ldots\ldots, W_r)$.

Hence, the total prediction error is also a function of W.

For every individual weight W_i, updation formula looks like

$W_{new} = W_{old} + \alpha * (\partial E / \partial W)|_{W_{old}}$ where α= learning parameter between 0 and 1.

(Fausett, 1994; Haykin, 1999; Smith and Gupta, 2000)

- ***Stopping rule***

There are two thumb-rules for stopping the iterations-

1. Stop if the decrease in total prediction error (since last cycle) is small.
2. Stop if the overall changes in the weights (since last cycle) are small.

(Fausett, 1994; Haykin, 1999; Smith and Gupta, 2000)

2.4 Application of Neural Network for Classification

ANNs have been used extensively over the past three decades for both classification and clustering (Sethi and Jain 1991: Jain and Mao 1994).

Kaski and Kohonen (1996) used self-organizing neural network to cluster the countries on the basis of welfare states and poverty level of the countries based on statistical data describing different aspect of standard of living. The data set was chosen to reflect as many aspects of standard of living as possible A total of 39 indicators were chosen to describe the factors like health, education, consumption and social services. The countries with similar quality of life factors were clustered together.

Spielman and Thill (2008) presented application of geographic information systems by integrating them with a data-mining technique to characterize populations in urban areas using large datasets. The self-organizing map algorithm was used to develop a geodemographic classification of a dataset containing 79 attributes describing census tracts in New York City. Through this classification, the complexity of New York's social landscape and insight into the relationship between geographic proximity and social similarity was observed.

Lin and Chen (2006) applied the self-organizing map to identify the homogeneous regions for regional frequency analysis. Self-organizing map, k-means method and ward's hierarchical method were tested to compare the cluster accuracy and SOM was found more robust than the traditional clustering methods.

Feed forward-back propagation neural networks are so versatile and can be used for data modeling, classification, forecasting, control, data and image compression, and pattern recognition (Hassoun, 1995). Heermann and Khazenie (1992) explored the suitability of a feed forward-back propagation neural network for classification of multispectral image data and Kavzoglu and Mather (2003) used feed forward-back propagation neural network for land cover classification. Benediktsson et al., (1990) classified multisource remote sensing and geographic data for evaluating performance of neural network and statistical methods in a comparative manner. Ripley (1994) identified feed forward-back propagation neural networks are now widely used in classification problems, whereas nonlinear methods of discrimination developed in the statistical field are much less widely known.

The literature shows that ANN is a widely applied method for solving clustering and classification problems. But no such study was conducted particularly in Bangladesh for classification of secondary cities, Paurashavas, based on the indicators focusing potentialities of the urban areas. The research seeks to develop an ANN model for classification of Paurashavas and the results of the research would be supportive for the government for formulating policy.

CHAPTER 3

RESEARCH METHODOLOGY

Chapter 3: Research Methodology

3.1 Introduction

Methodology illustrates the pre-scheduled, orderly steps of entire working procedure followed at different stages of the study to obtain the objectives of the research. Methodology used for developing the neural network model through functional classification of Paurashavas is described in this chapter. Identification of research problem, formulation of objectives, in-depth study of literature on related topics, selection criteria of different variables, sampling and collection procedure of data and algorithm used for developing neural network model are depicted under the three main phases of the research which are as follows:

- Conceptual Phase
- Data Collection Phase
- Model Development Phase

3.2 Conceptual Phase

The preliminary step of the research starts with identification of the research problem. Research problem has been identified by considering the existing classification system of Paurashava and available infrastructure and service facilities which accounts for devising an explicit and unambiguous classification of Paurashavas marked by accelerating urbanization by means of widely used neural network model. In order to develop a clear understanding of the functional characteristics of Paurashavas as well as concepts of neural network and its application for classification, an extensive literature survey and review has been conducted. In this stage of the research two objectives on the basis of which the research work would proceed is formulated.

3.3 Data Collection Phase

3.3.1 Selection of Variables

The aim of the research is to classify Paurashavas functionally on the basis of infrastructure and service facilities. Some basic functions amid compulsory and optional functions and non-agricultural characteristics of the Paurashava are considered to select variables for the research. Selected variables are standardized in terms of population, household or area in order to obtain accurate classification. The description of variables is summarized in Table 3.1.

In Bangladesh factors like (i) age of the Paurashava, (ii) extent of people engaged in non-agricultural activities, (iii) extent of revenue earning and expenditure by the Paurashava, (iv) total length of road and percentage of paved roads, (v) extent of water supply coverage and length of drainage, (vi) extent of electrification, (vii) existence of solid waste management system, (viii) availability and extent of health care services, (ix) community facilities etc. indicate the relative inferiority or superiority as well as serviceable efficiency of Paurashavas. Brief descriptions of these indicators are given hereunder.

Establishment Period

Functional efficiency of the Paurashavas is assumed to be increased with their establishment period so that age of Paurashavas is considered as a variable for functional classification.

Non-agricultural characteristic

One of the major conditions to consider an area as a Paurashava is, three fourths of the adult male population of the area must be employed mainly in non-agricultural occupations. Considering the non-agricultural characteristics of Paurashava, percentage of population 10 years and over engaged in non- agricultural activities and commercial and industrial land coverage are selected as variable for the research.

Financial aspect

Revenue earning and operational expenditure is vital for shaping functional effectiveness of Paurashava so that these factors are incorporated for determining the category.

Table 3.1: Description of Variables

Parameter	Variable	Definition
Establishment Period	Age	Current year - Establishment year
Non-agricultural characteristic	WorPop	% of population employed in non-agricultural activities
	LandUse	% of commercial and industrial land coverage
Financial aspect	Rev	Revenue (Tax, Rates. fees & others) per 1000 pop (Tk.)
	Exp	Operational expenditure per 1000 pop (Tk.)
Road	TotRd	Total Road per 10000 pop (km)
	PaveRd	% of Paved Road in respect of total road
Water Supply and Drainage	HHTap	% of household having tap water facility
	HHTube	% of household having tube well
	SurDrn	Surface Drain per 10000 pop (km)
Street Lighting	Epole	No. of electric pole per five km road
	ECov	Electrification coverage-Population (%)
	Elinelen	Line length of street lighting per 10000 pop (km)
Solid Waste	Dust	No. of Dustbin per 10000 pop
	ConCov	Conservancy Coverage-Population (%)
Health Service	Hosbed	No. of Hospital bed per 10000 pop
	Hcare	No. of Primary health care facility (Family planning centre and Maternity centre)
Community Service	Market	No. of Marketing facilities per 10000 pop

Road

Construction and maintenance of roads, bridges and culverts is the responsibility of Paurashava authorities. For this research the total length of road network and percentage of paved road are taken to signify the responsibility.

Water Supply and Drainage

Major tasks of Paurashava regarding water supply and drainage are to provide and regulate water supply system and to provide and maintain drainage system. In order to classify Paurashava on the basis of well-organized municipal services, households having tap water facility and tube well and length of surface drain are selected as the indicators which reveal the availability of water supply and drainage facilities.

Street Lighting

Number of electric pole, electrification coverage in terms of population and length of electric line for street lighting are selected as variables to explain the functions of Paurashava concerning provision and maintenance of street lighting.

Solid Waste

Solid waste management through removal, collection and disposal of refuse, waste and rubbish is one of major municipal services provided by the Paurashavas. Numbers of dustbin and conservancy coverage in terms of population related to this service are chosen as variables for the research.

Health Service

In order to explain the availability of health care services in the Paurashavas, number of hospital bed and number of primary health care facility (Family planning centre and Maternity centre) are considered as variables.

Community Service

Paurashavas are responsible for providing and maintaining community services specially marketing facilities. Availability of marketing facilities is preferred as indicators for determining functional classification of Paurashavas.

3.3.2 Sampling of Data

There were 254 Paurashavas (as of July. 2001) in Bangladesh (NILG. 2002). Due to unavailability of data of all Paurashavas on the above mentioned variables, sample data set has been selected by following stratified sampling method.

In the stratified sampling method the sample is representative of the population so that sample results can be generalized (Neuman, 1997; Sufian, 1998). In the existing classification system, Paurashavas are divided into three mutually exclusive groups, called strata (Class A, Class B and Class C). A random sample is drawn from each stratum and 125 Paurashavas has been selected in such a way that proportional distribution of Classes remains relatively same in the sample data set (Table 3.2).

Table 3.2: Stratified Sampling of Paurashavas

Class	Existing Classification		Sample data set	
	No.	Percentage	No.	Percentage
A	63	24.8	35	28
B	36	14.2	22	17.6
C	155	61	68	54.4
Total	254	100	125	100

3.3.3 Data Collection

Available data on selected variables have been collected from Paurashava Statistical Year Book, '98-99, published by National Institute of Local Government (NILG) (Appendix A).

3.4 Model Development Phase

In order to develop neural network model through classification of Paurashavas, both unsupervised learning and supervised learning algorithm of neural network have been used.

3.4.1 Self-organizing Neural Network for Clustering of Paurashavas

Self-Organizing Map (SOM) belongs to the category of competitive learning networks and is based on unsupervised learning. SOM is used for clustering data without knowing the class memberships of the input data.

Altogether selected eighteen variables describing functional characteristics of Paurashavas are used as input vectors. The complex joint effect of these factors has been obtained by organizing the Paurashavas in three groups or cluster units using the self-organizing map algorithm of neural network which perform categorization by learning the trends and relationships within data.

Paurashavas that have similar values of the variables are clustered in group. According to SOM algorithm, each Paurashava is in fact automatically assigned to a cluster describing its functional characteristics in relation to other Paurashavas.

NeuroXL Classifier software by AnalyzerXL following self-organizing neural networks has been used for classification of Paurashavas.

3.4.2 Development of Neural Network Model

In order to develop neural network model, cluster memberships of Paurashava acquired by using SOM algorithm is used as output vector. Supervised learning based Feed forward-Back propagation algorithm of neural network has been used for formulating neural network model using NeuroShell Classifier (Ward Systems Group, Inc) software package.

CHAPTER 4

FUNCTIONAL CLASSIFICATION OF PAURASHAVAS

Chapter 4: Functional Classification of Paurashavas

4.1 Introduction

In Bangladesh the classification of Paurashavas into groups is made on the basis of revenue earned. This classification recognized the taxable resources of a Paurashava but failed to reflect the quality of life the Paurashava offered to its citizen. The superiority of any Paurashava depends upon how well the inhabitants can live there There living conditions however, depend upon a number of provisions and facilities provided by the Paurashava authorities. Some of these facilities and provisions are: paved road, drainage, water supply, supply of electricity, solid-waste disposal, healthcare facilities, market facilities, non-agricultural activities etc. Needless to mention that no idea about these facilities can be obtained only through the amount of revenue earned by any Paurashava from the government classification system.

The Paurashavas of Bangladesh has been classified into the three classes as per criterion followed by the government (LGED, 2001). In this chapter attempt has been made to reclassify these Paurashavas by using Artificial Neural Network (ANN) on the basis of eighteen criterions. Then the new classification has been compared with the government classification to find out whether or how far these two vary. In case of drastic variations, endeavors will be made to find out its possible reasons.

4.2 Government (Existing) Classification of Paurashavas

Revenue is collected mainly by means of imposing tax, rates, fees on building, land, utility and community facilities etc. Paurashavas levy taxes, rates and fees for revenue earning. Paurashavas impose tax on annual value of buildings and lands, on transfer of immovable property. on applications for the erection and re- erection of buildings. on professions. trades and callings. on amusements. vehicles, animals, advertisements and on births, marriages, adoption and feasts. Out of these the first three and vehicle tax constitute major portion of revenue of Paurashavas (LGED, 2001). Rates are collected from lighting, conservancy and water supply facilities. Fees are collected from markets, licenses for slaughter of animals, from fairs, exhibitions and from schools. Other revenues include rates and profits from own property, interest from investment, fines etc.

Selected 125 Paurashavas of Bangladesh have been classified by the government of Bangladesh on the basis of this revenue earning capability into three Classes. For our purpose of study, these Paurashavas have been reclassified according to neural network. In order to differentiate between the two, the traditional division by the government of Bangladesh is mentioned as Class A, Class B and Class C, and that by neural network as Class I, Class II and Class III. Table 4.1 shows the classification of selected 125 Paurashavas as per Bangladesh government.

Table 4.1: Government (existing) Classification of Selected Paurashavas as of July 2001

Class	No. and % of Paurashavas	Name of Paurashavas
A	35 28%	Bhola, Bogra, Brahmanbaria, Cox's Bazar, Dinajpur, Faridpur, Habiganj, Jamalpur, Jessore, Joypurhat, Kishoreganj, Madaripur, Magura, Munshiganj, Mymensingh, Natore, Nawabganj, Pabna, Pirojpur, Patuakhali, Saidpur, Sherpur, Sirajganj, Sunamganj, Tangail, Bandarban, Bhairab, Chuadanga, Feni, Gazipur, Ishwardi, Jhenaidaha, Laksmipur, Naogaon, Thakurgaon
B	22 17.6%	Gaibandha, Mongla, Alamdanga, Bera, Gouripur, Hajiganj, Kadam Rasul, Kaliganj, Khagrachhari, Kurigram, Laksam, Lalmonirhat, Mohanganj, Nilphamari, Panchagar, Parbatipur, Patiya, Shariatpur, Gopalpur, Gurudashpur, Nalchity, Shibchar.
C	68 54.4%	Banaripara, Daulatkhan, Bheramara, Darsana, Kalapara, Kalia, Patgram, Shahjadpur, Shaestaganj Sharishabari, Barura, Betagi, Bhanga, Bhuapur, Burhanuddin, Chandina, Charfassion, Charghat, Chatmohar, Chhatak, Chhengarchar, Damudya, Dewanganj, Dhanbari, Durgapur, Galachipa, Ghatail, Ghorashal, Gobindoganj, Ishwarganj, Jibannagar, Kabirhat, Kalaroa, Kendua, Kotalipara, Kulaura, Madhabpur, Madhupur, Matlab, Mehendiganj, Mirkadeem, Mirpur, Manirampur, Nabiganj, Nalitabari, Nandail, Naria, Paikgachha, Panchbibi, Pangsha, Pirganj, Ramganj, Raozan, Rohanpur, Santahar, Santhia, Shahrasti, Shailkupa, Sariakandi, Shibganj, Shitakundu, Singra, Swarupkathi, Tanore, Trishal, Tungipara, Ulipur, Ullahpara.

Source: NILG, 2002

4.3 Classification by Self-Organizing Neural Network

In order to take any investment decision and development policy regarding in any Paurashava. it is essential to explore its real functional characteristics as may be manifested through available infrastructure and service facilities as well as non-agricultural activities.

Neural networks are a proven, widely used technology to solve complex classification problems. Self-organizing maps (SOM) belong to a general class of neural network methods, which are nonlinear regression techniques that can be applied to find relationships between inputs and outputs or organize data so as to disclose so far unknown patterns or structures (Khan et al., 2009).

In practical data analysis problems the most common task is to search for dependencies between variables. In such problems, SOM can be used for getting insight to the data and for the search of potential dependencies. Mangiamell et al., (1996) compared SOM and several hierarchical clustering methods, and found SOM superior to hierarchical clustering in both robustness and accuracy.

SOM neural network algorithm is applied to group the Paurashavas based on the eighteen independent variables (as mentioned in Chapter 3) into three classes or clusters: Class I, Class II and Class III (Figure 4.1). The grouping is done by minimizing the sum of squares of distances between data and the clusters weight space as the square error of each data point is calculated and clusters reformed such that the sum of square errors is made to be minimized. Detail algorithm of SOM is given in Chapter 2.

In the SOM algorithm, Kohonen (1989) proves that the value of the weights in the weight space will converge to a unique limit. Learning rate in SOM algorithm is a value between 0 and 1 that affects the rate at which the network starts learning. Smaller learning rates tend to slow the learning process while larger learning rates may cause network oscillation and non-convergence in the weight space (Zhang et al., 1998; Basheer & Hajmeer, 2000). So, learning rate for classification of Paurashavas is set 0.5 initially.

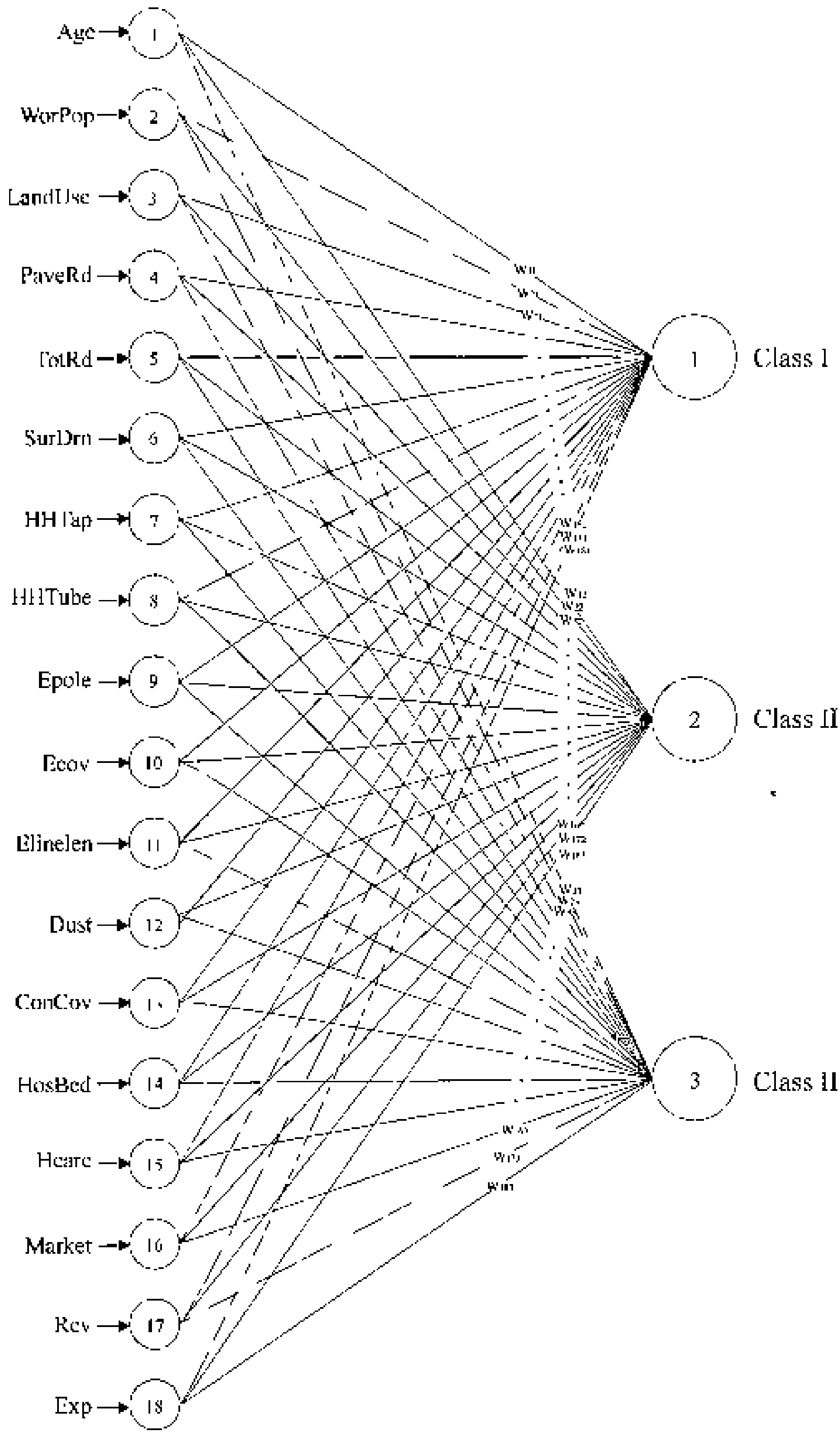


Figure 4.1: Self-organizing Neural Network Structure for Clustering of Paurashavas

In order to determine the relationship between inputs and outputs of a node and a network, sigmoid (logistic) function is the most popular choice among the different activation functions (Zhang et al., 1998). There are some heuristic rules for the selection of the activation function. Klimasauskas (1991) suggests sigmoid (logistic) activation functions for classification problems which involve learning about average behavior. The sigmoid (logistic) activation function seems well suited for many classification problems (Zhang et al., 1998). So, for this research sigmoid activation function has been applied.

In order to classify Paurashavas, NeuroXL Classifier software (Figure 4.2) has been used which implements self-organizing neural networks and performs categorization by learning the trends and relationships within data.

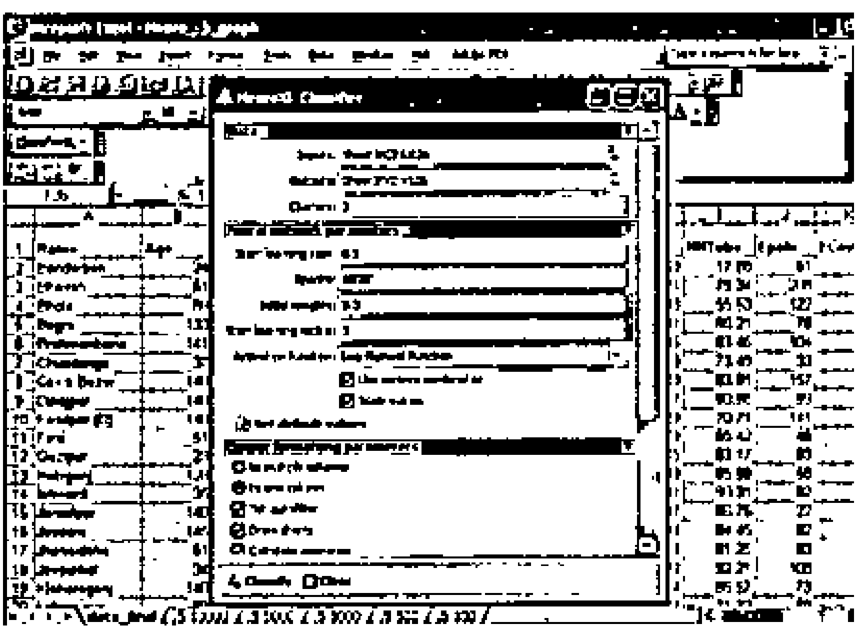


Figure 4.2: Interface of NeuroXL Classifier for Classification of Paurashavas

Using the Log-Sigmoid activation function, the SOM network is applied to classify Paurashavas with learning rate 0.5 and several iteration cycles. The classification of Paurashavas is fine tuned by using more epochs or iteration cycles. There happens no change in class distribution for epochs (Iteration cycles) over 500 (Table 4.2).

Table 4.2: Percentage Distribution of Paurashavas for different Epochs (Iteration Cycle) at learning rate 0.5

Epochs (learning rate 0.5)	Class		
	I	II	III
100	20.00	24.80	55.20
500	19.20	25.60	55.20
1000	19.20	25.60	55.20
5000	19.20	25.60	55.20
10000	19.20	25.60	55.20

By applying self-organizing neural network Paurashavas are grouped into three distinct categories- Class I, Class II and Class III. The complex joint effect of the selected factors is observed by organizing the Paurashavas by using the self-organizing neural network. Paurashavas that have similar values of the indicators are grouped together. Paurashavas with superior condition of factors as well as facilities are found in the upper class (Class I) and Paurashavas having poorer facilities are clustered in the lower class (Class III). In this classification, twenty four (19.2%) Paurashavas belong to Class I, thirty two (25.6%) Paurashavas assign to Class II and sixty nine (55.2%) Paurashavas belong to Class III.

In order to make comparison between the existing classes of Paurashavas and those obtained by self-organizing neural network (NN), the number of classes (gradation) have been kept the same which is three. Table showing comparison between neural network and existing classification for selected Paurashavas has been given in Appendix B

After applying self-organizing neural network the 125 Paurashavas have been found to be different in point of gradation or class. The new distribution of Paurashavas is provided in Table 4.3.

Table 4.3: Classification of Paurashavas by Applying Self-Organizing Neural Network

Class Using NN	No. and % of Paurashavas	Name of Paurashavas
I	24 19.2%	Bhola, Bogra, Brahmanbaria, Cox's Bazar, Dinajpur, Faridpur, Habiganj, Jamalpur, Jessore, Joypurhat, Kishoreganj, Madaripur. Mymensingh, Natore, Nawabganj, Pabna, Pirojpur, Patuakhali, Saidpur, Sherpur. Sunamganj, Sirajganj, Tangail, Gaibandha.
II	32 25.6%	Bandarban, Bhairab, Feni, Gazipur, Ishwardi. Jhenaidaha, Laksmipur, Magura, Munshiganj, Thakurgaon, Alamdanga, Gouripur, Kadam Rasul, Khagrachhari, Kurigram. Lalmonirhat, Mohanganj, Mongla, Nilphamari, Panchagar, Parbatipur, Patiya. Shariatpur, Banaripara, Daulatkhan, Galachipa, Ghorashal. Kalapara, Mirkadeem, Raozan Shitakundu Tungipara.
III	69 55.2%	Chuadanga, Naogaon. Bera, Gopalpur, Gurudashpur, Hajiganj, Kaliganj, Laksam, Nalchity, Shibchar, Barura, Betagi, Bhanga, Bheramara, Bhuapur, Burhanuddin, Chandina, Charfassion, Charghat, Chatmohar, Chhatak, Chhengarchar, Damudya, Darsana, Dewanganj, Dhanbari, Durgapur, Ghatail, Gobindoganj, Ishwarganj, Jibannagar, Kabirhat, Kalaroa, Kalia, Kendua, Kotalipara. Kulaura, Madhabpur, Madhupur, Matlab, Mehendiganj, Mirpur, Manirampur. Nabiganj. Nalitabari, Nandail, Naria, Paikgachha, Panchbibi, Pangsha, Patgram, Pirganj, Ramganj, Rohanpur, Santahar, Santhia. Shahrasti, Shahjadpur, Shailkupa, Shaestaganj, Sariakandi, Sharishabari, Shibganj, Singra, Swarupkathi, Tanore, Trishal, Ulipur, Ullahpara.

4.3.1 Performance Measures of Classified Paurashavas

Value of mean and standard deviation (i.e. root mean square error) of each variable has been used to measure the performance of classes of Paurashavas in neural network classification and existing classification in a comparative manner.

In the existing classification, the only criteria to determine the classification of Paurashavas is revenue, such that Paurashavas in a particular group are homogenous or compact with respect to this factor. On the other hand, in Neural Network (NN) method as many as eighteen variables expressing infrastructure and service facilities have been considered, where revenue earning is one factor only. Naturally, the Paurashavas belonging to each class of the NN category are homogenous or compact in respect of these variables. In Table 4.4 the values of mean indicating extent of available facilities as well as superiority of variables for each class in existing classification and neural network classification have been shown in a comparative manner.

Table 4.4: Comparison of Mean Value of Selected Variables between Existing Class and Neural Network (NN) Class

Variables	Mean Values					
	Class A	Class I	Class B	Class II	Class C	Class III
Age	93.8	**120.54***	*31.55*	29.28	13.78	**15.71**
WorPop	37.09	**37.35**	33.41	**35.85**	30	**31.48**
LandUse	12.73	**14.06**	*17.2*	16.9	*13.27*	12.29
PaveRd	60.96	**63.5**	57.44	**65.6**	*38.56*	34.73
TotRd	*13.39"*	12.25	*15.61*	14.58	17.4	**17.9**
SurDm	5.02	**5.53**	4.34	**4.57**	2.5	**2.85**
HHTap	*16.34*	15.88	6.78	**11.79**	*8.49*	7.83
HHTube	75.59	**77.48**	*76.7*	74.02	81.09	**81.44**
Epole	94.63	**97.58**	43.95	**63.44**	*44.04*	42.06
ECov	67.51	**69.92**	58.23	**61.91**	*48.91*	47.99
Elinelen	7.43	**8.16**	4.68	**5.22**	4	**4.14**
Dust	7.97	**8.54**	7.91	**9**	*6.68*	6
ConCov	59.54	**64.5**	51.77	**53.19**	36	**37.54**
HosBed	19.91	**21.5**	14.73	**21.5**	*17.1*	14.2
Hcare	2.94	**3.21**	2.14	**2.19**	1.44	**1.46**
Market	2.17	**2.39**	1.7	**1.81**	2.43	**2.44**
Rev	88276.54	**99464.08**	*63017.36*	57483.34	47776.57	**50699.46**
Exp	*110043.9*	106666.63	*81169.59*	79671.75	50095.78	**57018.65**

Note: * indicates bold numbers having larger mean values of different variables in neural network class (Class I, Class II and Class III)
" indicates italic numbers having larger mean values of different variables in existing class (Class A, Class B and Class C)

Paurashavas in the class having larger mean value of variables than other corresponding class contain improved facilities and are capable of providing greater urban services. From the Table 4.4 it is evident that neural network classification provides larger mean value for most of the variables than existing classification. For example, average conservancy coverage (ConCov) of Paurashavas in existing Class A is 59.54%, whereas Paurashavas in neural network Class I has 64.5% conservancy coverage. Also percentage of household having tap water facility in the existing Class B Paurashavas is 6.78, whereas the same in the neural network Class II Paurashavas is 11.79.

In Table 4.5 standard deviation indicating variability of data in each class of the existing classification and neural network classification have been shown in a comparative manner.

Table 4.5: Comparison of Standard Deviation of Selected Variables between Existing Class and Neural Network Class

Variables	Values of Standard Deviation					
	Class A	Class I	Class B	Class II	Class C	Class III
Age	46.68	**29.97**[*]	18.59	**16.17**	*4.27*	7.04
WorPop	5.16	**4.46**	7.62	**6.6**	6.2	**6.1**
LandUse	*10.47*[#]	10.58	*9.07*	10.57	8.87	**8.17**
PaveRd	17.04	**14.96**	19.26	**16.32**	20.11	**16.01**
TotRd	7.09	**5.48**	7.36	**7.09**	7.6	**7.51**
SurDrn	3.21	**3.16**	4.16	**3.88**	2.61	**2.49**
HHTap	14.17	**13.31**	*11.39*	13.33	5	**4.65**
HHTube	16.43	**13.35**	21.64	**20.6**	*8.56*	9.57
Epole	46.87	**43.52**	*35.61*	46.17	24.16	**24.03**
ECov	19.28	**17.26**	20.26	**16.83**	*17.05*	18.42
Elinclen	3.97	**3.88**	3.85	**2.89**	*1.86*	2.53
Dust	6.45	**6.32**	6.99	**6.95**	4.49	**4.17**
ConCov	17.01	**16.39**	20.74	**16.14**	15	**14.25**
HosBed	12.3	**11.24**	*8.81*	14.09	10.96	**8.13**
Hcare	1.28	**1.18**	1.31	**1.25**	0.74	**0.74**
Market	*1.67*	1.86	1.08	**1.03**	2.02	**2.01**
Rev	*160562.2*	194184.6	42029.74	**29684.84**	*23517.59*	27354.62
Exp	50790.41	**50477.89**	*32934.45*	48835.56	*29077.43*	32881.01

Note: [*] indicates bold numbers having smaller values of standard deviation of different variables in neural network class (Class I, Class II and Class III)

[#] indicates italic numbers having smaller values of standard deviation of different variables in existing class (Class A, Class B and Class C)

Standard deviation is the measure of determining how data is distributed. or how far each data is from the mean. For each class of Paurashavas in both existing and neural network classification, standard deviation has been calculated. Smaller standard deviation is the indication of data compactness. From the Table 4.5 it may be seen that in the neural network classification standard deviation is smaller for most of the variables, where as the deviation is considerable in case of existing classification. That indicates that the value of the variables for the Paurashavas in different classes is more homogenous and compact in neural network classes, in comparison to those in the existing classes. For example. standard deviation of Paurashavas in existing Class A for the variable percentage of paved road (PaveRd) is 17.04, while standard deviation in neural network Class I is 14.96.

From the Table 4.6 it can be summarized that for top grade Paurashavas (Class A or Class I), out of eighteen variables, mean value of fifteen variables have found larger in case of neural network classification than those in the existing classification. The value of standard deviation in case of neural network classification has been found to be smaller in fifteen variables. So. it is clear that neural network Class I is more compact than existing Class A with respect to the selected variables. For the Second grade (Class B or Class II) Paurashavas, 66.7% variables have been found to have larger mean value and 72.2% variables. smaller standard deviation in neural network classification. Similar depiction is observed for third grade (Class C or Class III) Paurashavas. Thus the neural network provides better classification of Paurashava in cases of mean value and value of standard deviation.

Table 4.6: Distribution of Variables according to Difference in Mean and Standard Deviation

Extent of Change	Class I_Class A	Class II_Class B	Class III_Class C
Difference in Mean			
Mean_NN*>Mean_Exis#	15 (83.3%)	12 (66.7%)	11(61.1%)
Mean_NN<Mean_Exis	3 (16.7%)	6 (33.3%)	7 (38.9%)
Difference in Standard Deviation (SD)			
SD_NN<SD_Exis	15 (83.3%)	13 (72.2%)	12 (66.7%)
SD_NN>SD_Exis	3 (16.7%)	5 (27.8%)	6 (33.3%)

Note: *indicates NN = Neural Network Classes of Paurashavas
# indicates Exis = Existing Classes of Paurashavas

4.3.2 Characteristics of Classified Paurashavas

Paurashavas with similar characteristics in case of selected variables have been grouped together. In order to determine the characteristics of Paurashavas belonging different classes in existing classification and neural network classification, weighted average (%) of each variable has been compared among classes. Weighted average (%) for each variable of any class indicates how many times larger or smaller it is, compared to the weighted average of this variable in all three classes (Appendix C).

For example, weighted average value of the variable of conservancy coverage (ConCov) for the Paurashavas of all classes (Class A, Class B and Class C) is 45.4 in the existing classification and average conservancy coverage of Paurashavas belonging to Class A, Class B and Class C are 59.54, 51.77 and 36 respectively. Average conservancy coverage of Class A Paurashavas is 31.24 times larger, Class B Paurashavas is 14.11 times larger and Class C Paurashavas is 20.65 times smaller than the weighted average value of the variable for all classes.

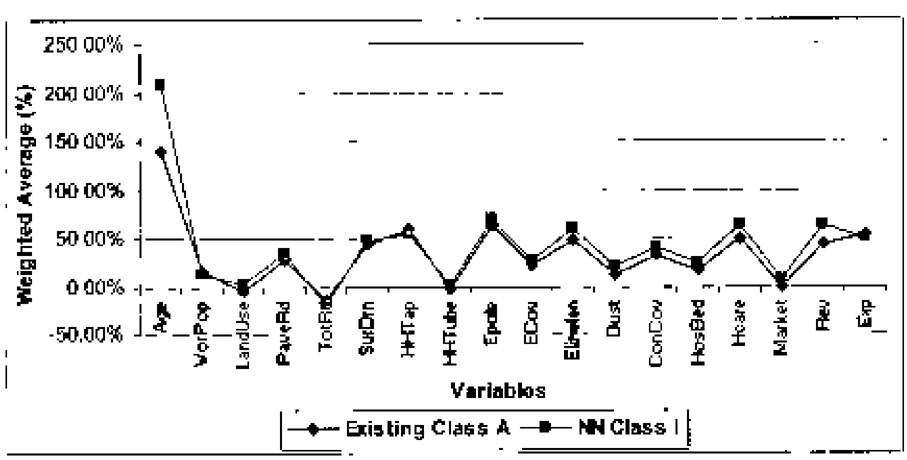


Figure 4.3: Comparison of Weighted Average (%) between Existing Class A and NN Class I

The weighted average (%) of eighteen variables in case of neural network and existing classifications for Class A and Class I have been shown in Figure 4.3. It is evident that neural network Class I contains Paurashavas having above average values for 88.9% indicators and below average value for 11.1% indicators whereas existing Class A comprises Paurashavas with above average value for 77.8%

indicators and below average value for 22.2% indicators. Weighted average (%) value of a good number indicators is larger in neural network Class I than existing Class A.

In the above figure it is found that Paurashavas under neural network Class I have not only larger revenue earning, but also have larger provision of infrastructure and urban facilities (such as non agricultural land use, percentage of paved road, length of surface drain. water supply facilities including both tap and tube well, number of electric pole and dusthin, electrification and conservancy coverage, electric line length, number of hospital bed, healthcare centre and market facilities etc.) than Paurashavas under existing Class A. It means that financial condition of the Paurashavas under neural network Class I is satisfactory and they also play the leading role for providing infrastructure and service facilities.

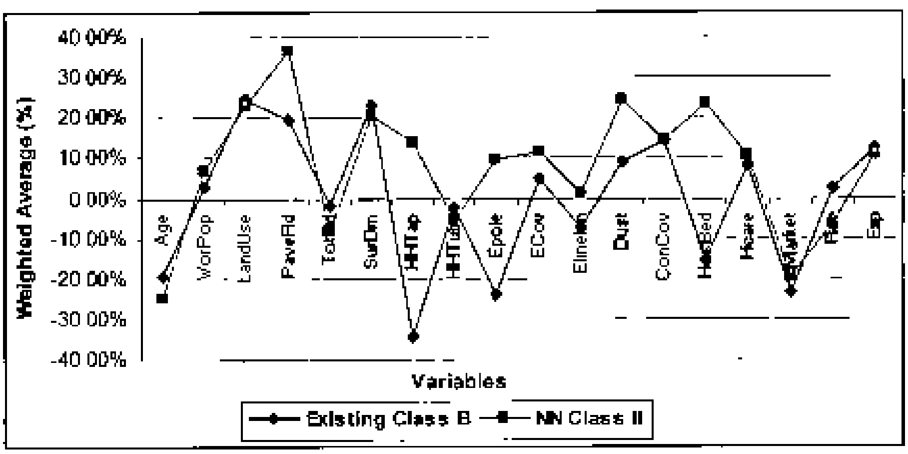


Figure 4.4: Comparison of Weighted Average (%) between Existing Class B and NN Class II

In Figure 4.4 weighted average (%) of eighteen variables for Class II in neural network and Class B in existing classification has been compared. It may be seen that Paurashavas in neural network Class II have above average values for 72.2% indicators and below average value for 27.8% indicators. whereas existing Class B comprises Paurashavas with above average value for 55.6% indicators and below average value for 44.4% indicators.

Although revenue earning of Paurashavas belonging to neural network Class II is less than the Paurashavas belonging to existing Class B, provision of infrastructure and service facilities for the Paurashavas under neural network Class II is extensive and better than Paurashavas under existing Class B. It means that the financial condition of the Paurashavas under existing Class B is satisfactory, but they fail to provide infrastructure and service facilities. Differences in weighted average (%) values of indicators between two classes are significant particularly for the factors-percentage of paved road, percentage of household having tap water facility, number of electric pole and dustbin, length of electric line, number of hospital bed and healthcare centre and also electrification coverage. It indicates that Paurashavas assigning to neural network Class II are able to provide sufficient urban facilities than Paurashavas belonging to existing Class B, so that Class II Paurashavas are in better conditions in terms of infrastructure and service facilities.

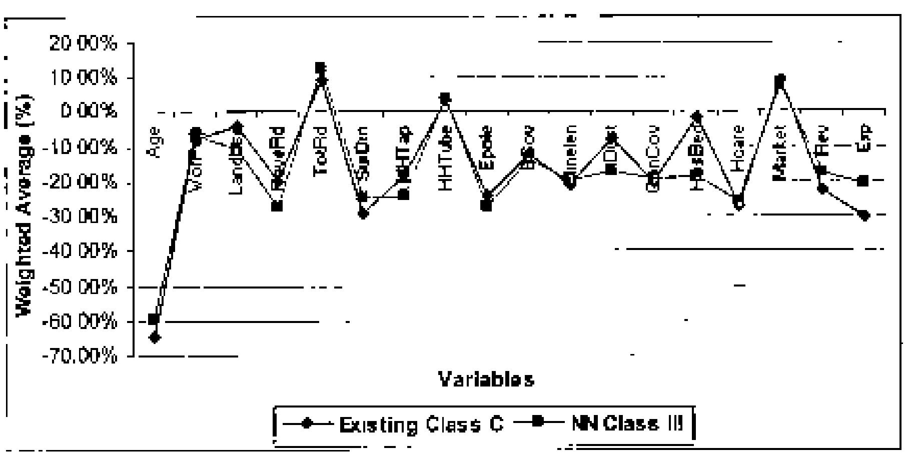


Figure 4.5: Comparison of Weighted Average (%) between Existing Class C and NN Class III

From the Figure 4.5, it is clear that both neural network Class III and existing Class C contains Paurashavas having above average values for 16.7.% indicators (larger length of total road, percentage of household having tap water facility and number of marketing facilities) and below average value for rest 83.3% indicators

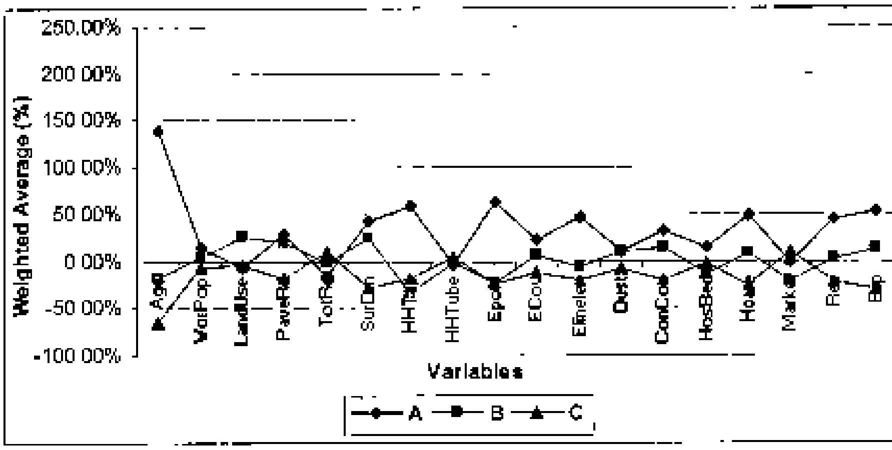


Figure 4.6: Comparison of Weighted Average (%) among Existing Classes of Paurashavas

In Figure 4.6, comparison of weighted average (%) among the existing classes of Paurashavas has been shown. In this figure it is found that the average values of variables in case of three classes vary abruptly. However, the variables in case of three classes do not significantly express the hierarchy.

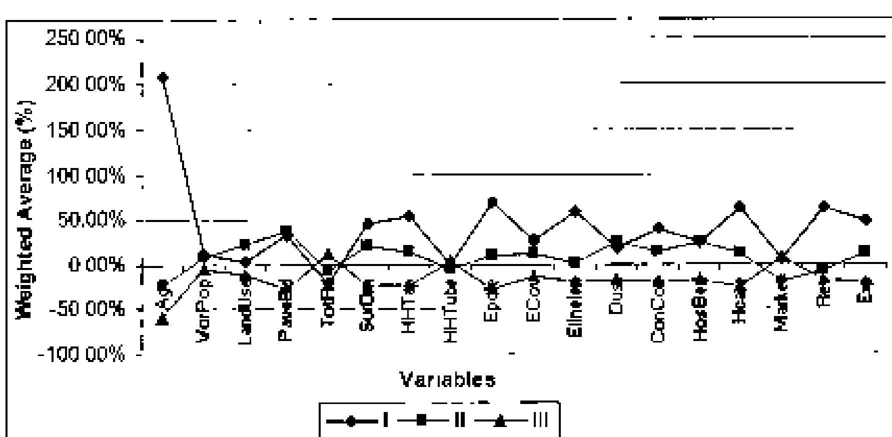


Figure 4.7: Comparison of Weighted Average (%) among NN Classes of Paurashavas

In Figure 4.7, comparison of weighted average (%) among the neural network classes of Paurashavas has been shown. In this figure it is found that the average values of variables in case of three classes vary gradually and follow distinct hierarchy. However, distinct dissimilarity can be seen among classes of different grades.

4.3.3 Extent of Class Change

Paurashavas that belong to higher or lower categories than the corresponding classes are compared and reasons behind this have been explained with respect of variation of mean values for each variable. Variation of mean value has been calculated in percent (Table 4.15). It can be inferred from this value that how many times smaller or larger average value of each variable for shifted Paurashavas from a particular class of existing classification, compared to the average of each variable for the corresponding class in neural network classification.

For example, suppose ten Paurashavas are shifted from existing Class A to neural network Class II. In order to determine the reason for not belonging of these Paurashavas to the corresponding neural network Class I, mean variation between average of each variable for shifted Paurashava and that of for neural network Class I is determined.

Table 4.7: Comparison between Existing Class A and NN Class I, II, III

Existing Class	Classification by Neural Network (NN)		
	I	II	III
A	Bhola, Bogra, Brahmanbaria, Cox's Bazar, Dinajpur, Faridpur, Habiganj, Jamalpur, Jessore, Joypurhat, Kishoreganj, Madaripur, Mymensingh, Natore, Nawabganj, Pabna, Pirojpur, Patuakhali, Saidpur, Sherpur, Sunamganj, Sirajganj, Tangail.	Bandarban, Bhairab, Feni, Gazipur, Ishwardi, Jhenaidaha, Laksmipur, Magura, Munshiganj, Thakurgaon.	Chuadanga, Naogaon.

Table 4.7 depicts that among thirty five existing Class A Paurashavas 67.5% Paurashavas remain in same hierarchy (Class I) and 34.3% Paurashavas fall under the lower hierarchy (Class II and Class III).

Reasons for Shifting from Class A to Class II

Bandarban, Bhairab, Feni, Gazipur, Ishwardi, Jhenaidaha, Laksmipur, Magura, Munshiganj and Thakurgaon Paurashavas are the Class A Paurashavas in the existing classification but in neural network classification these Paurashavas shift their class from existing Class A to neural network Class II.

In order to find the underlying reasons behind shifting of Class A to lower order (i.e. not belonging to the corresponding neural network class), mean values of neural network Class I Paurashavas for selected indicators have been compared with the mean values of these changed ten Paurashavas (Table 4.15). For 83.3% indicators, these ten Paurashavas have lower average value than average of Class I Paurashavas. These indicators are given in Table 4.8.

Table 4.8: Reasons for Shifting from Class A to Class II

Indicators having lower mean values	
Establishment period	Electrification coverage
Percentage of non-agricultural land use	Number of dustbin and electric pole
Percentage of working population involved in non-agricultural activities	Conservancy coverage
Length of surface drain	Number of market facilities
Percentage of household having tube well facilities	Number of hospital bed and healthcare centre
Length of electric line	Revenue

The table proves that these ten Paurashavas though have required revenue earning capability for being Class A Paurashavas but non-agricultural characteristics of Paurashavas is not satisfactory and also they do not provide adequate utility and community facilities to the urban dwellers like a first class Paurashavas.

Reasons for Shifting from Class A to Class III

Chuadanga and Naogaon Paurashavas assign to Class A Paurashavas in the existing classification but the neural network classification suggests that they should be in lowest category (Class III).

For 83.3% indicators, these two Paurashavas show extremely lower average value than average of neural network Class I Paurashavas (Table 4.15). These indicators are given in Table 4.9.

Table 4.9: Reasons for Shifting from Class A to Class III

Indicators having considerable lower mean values	
Establishment period	Electrification coverage
Percentage of non-agricultural land use	Number of dustbin and electric pole
Percentage of working population involved in non-agricultural activities	Conservancy coverage
Percentage of paved road	Number of market facilities
Percentage of household having tap water facilities	Number of hospital bed and healthcare centre
Length of surface drain	Revenue and Expenditure

These Paurashavas have very low average values for most of the indicators which indicates that these two Paurashavas fail to provide adequate utility and community facilities to the urban dwellers and also to prove the non-agricultural characteristics of Paurashavas like other Paurashavas belong to Class I.

Table 4.10: Comparison between Existing Class B and NN Class I, II, III

Existing Class	Classification by Neural Network		
	I	II	III
B	Gaibandha	Alamdanga, Gouripur, Kadam Rasul, Khagrachhari, Kurigram, Lalmonirhat, Mohanganj, Mongla, Nilphamari, Panchagar, Parbatipur, Patiya, Shariatpur	Bera, Gopalpur, Gurudashpur, Hajiganj, Kaliganj, Laksam, Nalchity, Shibchar

From the Table 4.10, it is evident that among twenty two existing Class B Paurashavas 59.1% Paurashavas are in same hierarchy (Class II). 4.5% Paurashavas lift to higher class (Class I) and 36.4% Paurashavas go down in the lower class (Class III).

Reasons for Shifting from Class B to Class I

Gaibandha Paurashava of existing Class B upgrade to neural network Class I. It has fairly higher average value for 77.8% indicators than average of Class II Paurashavas which is the corresponding of Class B in the existing classification (Table 4.15).

Table 4.11: Reasons for Shifting from Class B to Class I

Indicators having larger mean values	
Establishment period	Length of surface drain
Percentage of non-agricultural land use	Number of dustbin and electric pole
Percentage of working population involved in non-agricultural activities	Electrification coverage and Length of electric line
Percentage of paved road	Conservancy coverage
Length of total road	Number of market facilities
Percentage of household having tap water facilities	Expenditure

The indicators for which this Paurashava has larger average values are given is Table 4.11. It indicates that though revenue earning of this Paurashava is not satisfactory but the Paurashava has satisfactory provision of infrastructure and service facilities than other Paurashavas of Class II.

Reasons for Shifting from Class B to Class III

Bera, Gopalpur, Gurudashpur, Hajiganj, Kaliganj, Laksam, Nalchity and Shibchar Paurashavas are the Class B Paurashavas in the existing classification but in neural network classification these Paurashavas go down to neural network Class III. For 72.2% indicators, these eight Paurashavas have extremely lower average value than average of Class II Paurashavas (Table 4.15). These indicators are given in Table 4.12.

Table 4.12: Reasons for Shifting from Class B to Class III

Indicators having lower mean values	
Establishment period	Length of surface drain
Percentage of non-agricultural land use	Number of dustbin and electric pole
Percentage of working population involved in non-agricultural activities	Electrification coverage and Length of electric line
Percentage of paved road	Conservancy coverage
Percentage of household having tap water facilities	Number of hospital bed and healthcare centre

These eight Paurashavas have fulfill the standard of being existing Class B Paurashavas with respect to only revenue but non-agricultural characteristics of Paurashavas is not satisfactory and also they are not able to provide adequate utility and community facilities to the urban dwellers like the Paurashavas belong to Class II.

Table 4.13: Comparison between Existing Class C and NN Class I, II, III

Existing Class	Classification by Neural Network		
	I	II	III
C		Banaripara, Daulatkhan, Galachipa, Ghorashal, Kalapara, Mirkadeem, Raozan Shitakundu Tungipara	Barura, Betagi, Bhanga, Bheramara, Bhuapur, Burhanuddin, Chandina, Chartassion, Charghat, Chatmohar, Chhatak, Chhengarchar, Damudya, Darsana, Dewanganj, Dhanbari, Durgapur, Ghatail, Gobindoganj, Ishwarganj, Jibannagar. Kabirhat, Kalaroa, Kalia, Kendua, Kotalipara, Kulaura, Madhabpur, Madhupur, Matlab, Mehendiganj, Mirpur, Manirampur, Nabiganj, Nalitabari, Nandail, Naria, Paikgachha, Panchbibi, Pangsha, Patgram, Pirganj. Ramganj, Rohanpur, Santahar. Santhia, Shahrasti, Shahjadpur, Shailkupa, Shaestaganj, Sariakandi, Sharishabari, Shibganj, Singra. Swarupkathi, Tanore, Trishal, Ulipur, Ullahpara

From the Table 4.13. it is evident that among sixty eight existing Class C Paurashavas, 86.8% Paurashavas remain in same hierarchy (Class III) and 13.2% Paurashavas lifts to higher class (Class II).

Reasons for Shifting from Class C to Class II

Aa Banaripara, Daulatkhan, Galachipa. Ghorashal, Kalapara. Mirkadeem, Raozan Shitakundu and Tungipara Paurashava of existing Class C have higher average value for 72.2% indicators than average of Class III Paurashavas, this Paurashava promote to neural network Class II (Table 4.15).

The indicators for which this Paurashava has larger average values are given in Table 4.14. It indicates that revenue earning of this Paurashava is not satisfactory but this Paurashava has satisfactory provision of infrastructure and service facilities than the Paurashavas of Class III.

Table 4.14: Reasons for Shifting from Class C to Class II

Indicators having larger mean values	
Percentage of non-agricultural land use	Number of dustbin and electric pole
Percentage of working population involved in non-agricultural activities	Electrification coverage
Percentage of paved road	Length of electric line
Length of surface drain	Conservancy coverage
Percentage of household having tap water facilities	Number of hospital bed and healthcare centre

Table 4.15: Mean Variation between Shifted Paurashavas from Existing Class and Paurashavas of Neural Network Class

Variables	Mean Variation				
	Class I & Paurashavas shifted from Class A		Class II & Paurashavas shifted from Class B		Class III & Paurashavas shifted from Class C
	Class A to Class II	Class A to Class III	Class B to Class I	Class B to Class III	Class C to Class II
Age	-67.4	-65 57	193.72	-24 01	-19.35
WorPop	-0.62	-9.61	3.38	-21 65	6.89
LandUse	-12.73	-76.88	23.49	-9 78	65 09
PaveRd	-3 12	-51.98	0 99	-35.16	100.58
TotRd	14.61	122.73	39.78	18.28	-12.51
SurDrn	-26 94	-22.97	29 54	-61.95	18.25
HHTap	17.32	-13.66	94.06	-76.88	22.73
HHTube	-10.71	5 13	-7.35	11.84	-1 71
Epole	-2.34	-51.83	21 37	-61.18	1.45
ECov	-5 61	-24.91	29 22	-26.3	12.29
Elinelen	-28.06	24.5	186.9	-46.38	14.73
Dust	-13.35	-29.74	33.33	-37.5	79.67
ConCov	-20.93	-24.81	33.48	-35.14	18.38
HosBed	-16.28	-69 77	-44.19	-55 81	112.82
Hcare	-28.35	-22 12	-8.68	-31.51	6 85
Market	-19 67	-62.53	27 29	18.22	-27 05
Rev	-43.3	-26.27	-85.9	32.38	10.89
Exp	13 23	-12.87	28.15	8.25	-32.17

Note: * indicates values are in Percentage
(-) minus values indicates lower percentage than corresponding neural network class mean
(+) plus values indicates higher percentage than corresponding neural network class mean

In the Table 4.16 summary of the shifting of Paurashavas from existing class to neural network class is given.

Table 4.16: Comparison between Existing Classification and Neural Network Classification

Existing Classification		Classification by Neural Network		
Class	No	I	II	III
A	35	23 (65.7%)	10 (28.6%)	2 (5.7%)
B	22	1 (4.5%)	13 (59.1%)	8 (36.4%)
C	68		9 (13.2%)	59 (86.8%)

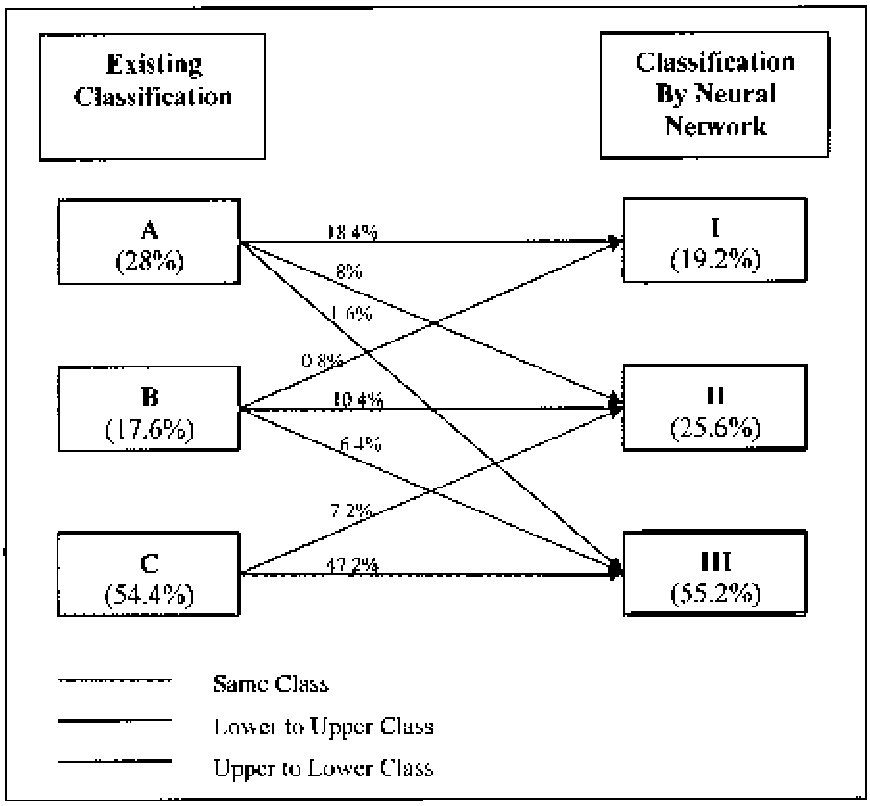


Figure 4.8: Shifting of Paurashavas from Existing Class to Neural Network Class

From the Figure 4.8, it is clear that in neural network classification, Class I contains 23 (18.4%) Paurashavas of existing Class A and 1 (0.8%) Paurashavas of existing Class B. Class II incorporates 10 (8%) Paurashavas of existing Class A. 13 (10.4%) Paurashavas of existing Class B and 9 (7.2%) Paurashavas of existing Class C. Class

III comprises 2 (1.6%) Paurashavas of existing Class A, 13 (6.4%) Paurashavas of existing Class B and 59 (47.2%) Paurashavas of existing Class C.

Table 4.17: Shifting of Paurashavas from Existing Class to Neural Network Class

Extent of Change	No. of Paurashavas	Percentage of Paurashavas
Same Class	95	76 %
Upper to Lower Class	20	16 %
Lower to Upper Class	10	8 %
Total	**125**	**100 %**

From the Table 4.17, it is obvious that among selected 125 Paurashavas for classification by using neural network algorithm, 76% Paurashavas remain in same hierarchy, 16% Paurashavas go down to lower hierarchy and only 8% Paurashavas lift to the upper hierarchy in neural network classification.

CHAPTER 5

DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK MODEL

Chapter 5: Development of Artificial Neural Network Model

5.1 Introduction

Artificial Neural Networks (ANNs) has been used in solving a variety of problems specially pattern classification, clustering and forecasting. In this research an attempt has been made to develop an Artificial Neural Network (ANN) model to classify Paurashavas of Bangladesh. Using various statistical parameters, the performance and accuracy level of reclassified Paurashavas has been validated.

5.2 Development of Model

Both supervised and unsupervised learning procedure has been employed to develop artificial neural network model (ANN) for classification of Paurashavas. Unsupervised learning method of neural network (i.e. Self-organizing neural network algorithm) has been applied to cluster or group the Paurashavas based on similarities of the selected independent variables into desired classes (Class I, Class II and Class III) (as mentioned in Chapter 4).

By using the classes of Paurashavas defined through applying self-organizing neural network. supervised learning method of neural network (i.e. Feed forward-Back propagation neural network algorithm) has been used to predict classes for Paurashavas (Figure 5.1). The goal of the algorithm is to understand the basis for the classification from a set of labeled Paurashavas and build a predictor for future unlabeled Paurashavas.

In order to develop neural network model, cluster memberships of Paurashava (Class I, Class II and Class III) acquired by using self-organizing neural network algorithm has been used as dependent variable i.e. output and selected eighteen variables has been considered as independent variables i.e. input. NeuroShell Classifier (Ward Systems Group, Inc) software package has been used to develop model.

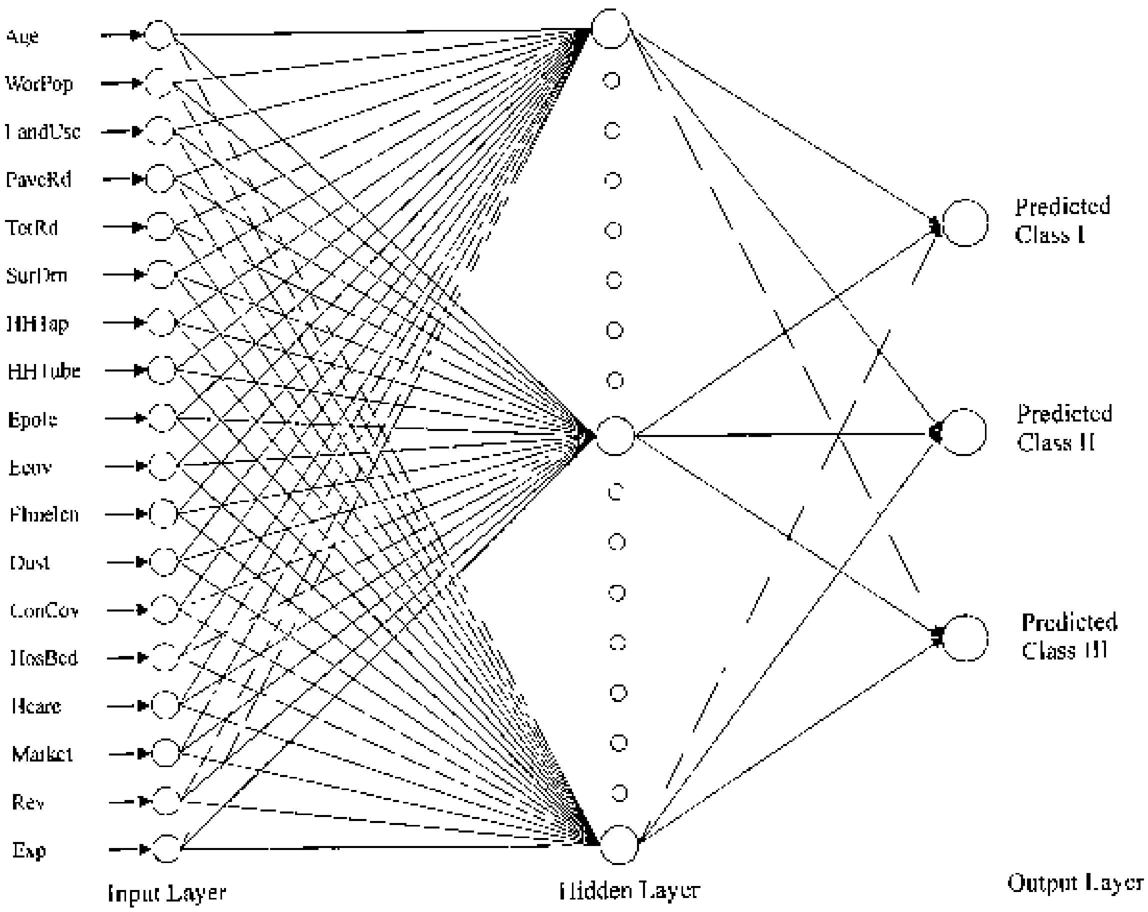


Figure 5.1: Feed forward-Back propagation Neural Network Structure for Class Prediction of Paurashava

5.2.1 Data set for the Model

For building the artificial neural network (ANN) classifier, the relevant data set has been divided into two separate subsets namely "training set" and "testing set".

The training set is used for ANN model development and testing set is adopted for evaluating the ability of the model for predicting class. The selection of the training and testing set affects the performance of ANN model (Mitra, 2008; Zhang et al., 1998). Both training set and testing set includes many sets of input variables and a corresponding output variable. The training data set should include a representative set of the problems likely to be encountered in the real world.

However, literature offers little guidance in selecting the training and test sample. Most authors select them based on the rule of 90% vs. 10%, 80% vs. 20% or 70% vs.

30%. etc (Zhang et al, 1998; Bounds, D. & Ross, D., 1997). Granger (1993) suggests that for nonlinear prediction model, at least 20 percent of any sample should be held back as testing set for prediction evaluation.

The data set used to develop the neural network model for Paurashavas in Bangladesh consists of a sample of 125 Paurashavas. The two samples for training set and testing set have been selected in such a way that both of the set represent entire data set. Thus proportional distribution of classes remains relatively same in the sample data sets compared to the entire data set (Table 5.1). To develop the model training set consists of 80% of the Paurashavas and the rest used for predicting classes of Paurashavas as suggested by Granger (1993).

Table 5.1: Number and Percentage of Paurashavas in Entire Sample, Training Sample and Testing Sample

Class	Entire Sample (125)		Training Set = 80% (100 of 125)		Testing Set = 20% (25 of 125)	
	No. of Paurashava	% of Paurashavas	No. of Paurashava	% of Paurashavas	No. of Paurashava	% of Paurashavas
I	24	19.2	19	19	5	20
II	32	25 6	26	26	6	24
III	69	55.2	55	55	14	56

Table 5.2 provides the descriptive statistics of the entire sample and the two subsets for training and testing From the table it is evident that there are no significant differences between the training and testing data subsets and each is a reasonable representation of the entire data set.

5.2.2 Performance of the Model

The Neural Training Strategy uses a neural net that dynamically grows hidden neurons to build a model which generalizes well. Performance of the model has been determined considering percentage of correct classification of the Paurashavas by the network. The network determines the correct classification by comparing its classification with the category specified for each Paurashavas in the training data and then summarizing the results for the entire training set. The best model indicates higher percentage of correct classification of Paurashavas.

Table 5.2: Descriptive Statistics of Entire Sample, Training Sample and Testing Sample

Variables	Mean			Standard Deviation		
	Entire Sample (125)	Training Set (100)	Testing Set (25)	Entire Sample (125)	Training Set (100)	Testing Set (25)
Age	39.31	37.86	45.12	43.27	41.42	50.53
WorPop	33.73	33.8	33.43	6.44	6.83	4.64
LandUse	13.81	13.86	13 6	9.43	9.6	8.92
PaveRd	48.15	48.13	48.24	21.75	22.05	20.93
TotRd	15.96	15.39	18.26	7.43	7.15	8.25
SurDrn	3.8	3 83	3 72	3.2	3.2	3.28
HHTap	10.39	10.82	8.67	9.96	10.82	5
HHTube	78.78	78 22	81	14.12	15.1	9.14
Epole	58.19	62.35	41.56	40.66	42.56	26.63
ECov	55.76	56.44	53.04	19.86	19.26	22.3
Elinelen	5.19	5.32	4.65	3.27	3.32	3.1
Dust	7.26	6.93	8.56	5.57	5.43	6.02
ConCov	46.72	47.71	42.76	18.58	19.37	14.67
HosBed	17.47	16.7	20.56	11.07	10.8	11.84
Hcare	1.98	2	1.92	1.2	1.22	1.12
Market	2.27	2.11	2.89	1.79	1.35	2 92
Rev	61798.94	65776.58	45888.4	89290.23	98610.71	27406.31
Exp	72350.26	71899 14	74154.72	45103.16	43979.93	50274 94

5.2.2.1 Training set

Training a neural network refers to the process of the model "learning" the patterns in the training data in order to make classifications. Training the network involves adding hidden neurons until the net is able to make good classifications. A small number of hidden neurons limit learning. If hidden neuron is set higher, the risk of over-training or over-fitting the model is experienced. The only method available to determine the optimum number of hidden neurons i.e. the number of hidden neurons that best solves the classification problem, is through trial and error (Worzala et al., 1995). Therefore, to find the optimum artificial neural network model, trial and error process has been applied.

Table 5.3: Neural Learning and Performance of Training Set

Model	Number of hidden neurons trained	Optimum number of hidden neurons	% of correct classification	% of incorrect classification
1	40	32	99	1
2*	60	44	100	0
3*	80	44	100	0

Note: * indicates the best result

While network is learning for the hidden neuron 40, network provides 99 percent correct classification of Paurashavas and in this case number of hidden neurons gives the best result is 32 (Model 1). But network can classify 100 percent Paurashavas correctly for the optimum hidden neurons of 44 (Model 2 & 3) (Table 5.3). Trained network with optimum hidden neurons of 44 has been applied to evaluate the model performance.

5.2.2.2 Testing set

The trained network with hidden neurons of 44 has been applied to the data of testing set. Network categorizes 96% Paurashavas accurately and error classification is only 4% (Table 5.4).

Table 5.4: Performance of Testing Set

Total Number of Paurashavas tested	Paurashavas classified correctly	% of correct classification	Paurashavas classified incorrectly	% of incorrect classification
25	24	96	1	4

For each Paurashava in testing set, performance of the network has also been measured in terms of probability values of belonging in a specific classification category. In the Table 5.5, classification category and the network classification value for each category has been shown.

Table 5.5: Probability Values of Classes for Paurashavas

Name of Paurashavas	Actual NNClass	Predicted NNClass by the Network	Class I	Class II	Class III
Jessore	I	I	1	0	0
Bogra	I	I	1	0	0
Jamalpur	I	I	1	0	0
Gazipur	II	II	0	1	0
Magura	II	II	0	1	0
Laksam	III	III	0	0	1
Ghatail	III	III	0	0	1
Kabirhat	III	III	0	0	1
Matlab	III	III	0	0	1
Pirganj	III	III	0	0	1
Sherpur	I	I	0.999	0	0.001
Kishoreganj	I	I	0.999	0	0.001
Nabiganj	III	III	0	0	0.999
Paikgachha	III	III	0.001	0	0.999
Gopalpur	III	III	0.002	0	0.998
Darsana	III	III	0	0.002	0.998
Burhanuddin	III	III	0	0.004	0.996
Panchagar	II	II	0.003	0.995	0.002
Lalmonirhat	II	II	0.003	0.991	0.006
Santhia	III	III	0	0.008	0.991
Shibchar	III	III	0	0.072	0.928
Kotalipara	III	III	0	0.082	0.918
Chatmohar	III	III	0	0.259	0.741
Daulatkhan	II	II	0	0.687	0.313
Gouripur*	II	I	0.85	0.003	0.147

Note. * Paurashava classified incorrectly by the network

The probability value is the neuron activation strength for each category based on the set of input values and the values for all categories add up to 1. When the value is close to 1 in a category, the network is more confident that the set of inputs belongs to that particular category. For example, the probability value of Sherpur Paurashava for classification category I is 0.999. It means that the network is more certain in assigning that Paurashavas in Class I.

5.2.3 Statistical Parameters of the Model

Statistical parameters of the model reflect the neural network performance as to compare to the actual classifications obtained by self-organizing neural network. These parameters apply to each output class separately.

The Paurashavas are classified by self-organizing neural network into three classes: Class I, Class II and Class III. These are called actual classifications for the model. Afterward a neural network model has been developed to make classifications for the same Paurashavas. The neural network does not necessarily give classifications which completely coincide with the actual classifications.

Table 5.6 shows the network classifications and the actual classification in the testing data file to which the network has been applied in a comparative manner. The column labels of the table, Actual I. Actual II and Actual III, refer to the category classification in the data file. The row labels of the table, Classified as I. Classified as II and Classified as III refer to the network class predictions.

When the network has been applied to 25 Paurashavas of testing data, there are:

- Five Paurashavas classified as Actual Class I, which the network has confirmed.
- Six Paurashavas classified as Actual Class II but the network has classified five of those Paurashavas as Class II and one as Class I.
- Fourteen Paurashavas classified as Actual Class III, which the network has confirmed.

Performance of the model for Paurashava has been evaluated on the basis of sensitivity and specificity.

Table 5.6: Agreement Matrix of the Model

	Actual "I"	Actual "II"	Actual "III"	Total
Classified as "I"	5	1	0	**6**
Classified as "II"	0	5	0	**5**
Classified as "III"	0	0	14	**14**
Total	**5**	**6**	**14**	**25**
True-pos. ratio	1.0	0.8333	1.0	
False-pos. ratio	0.05	0.0	0.0	
True-neg. ratio	0.95	1.0	1.0	
False-neg. ratio	0.0	0.1667	0.0	
Sensitivity	100.0%	83.33%	100.0%	
Specificity	95.0%	100.0%	100.0%	

In order to provide a clear understanding of the Table 5.6, the parameters for the Class I has been explained below from the comparison of the actual and neural network classifications. The same logic has also been applied to the definition of the Class II and Class III parameters.

True-pos. ratio (True-Positive Ratio, also known as Sensitivity)

The Paurashavas, which are classified by the neural network as Class I, and these Paurashavas actually belong to Class I. The neural network answers correctly in these cases. The True-positive ratio for Class I is a ratio of the total number of Class I true-positive classifications to the total number of actual Class I classifications.

True-positive ratio for Class I, Class II and Class III is 1.0, 0.8333 and 1.0 that means neural network responses correctly for all Paurashavas actually belonging to Class I and Class III but in case of actual Class II neural network responses correctly not for all Paurashavas.

False-pos. ratio (False-Positive Ratio)

The Paurashavas, which are classified by the neural network as Class I, but these Paurashavas actually do not belong to Class I (they belong to Class II or Class III). The neural network answers incorrectly in these cases; these are misclassifications. The False-positive ratio for Class I is a ratio of the total number of Class I false-positive classifications to the total number of actual classifications in all classes other than Class I.

False-positive ratio for Class I, Class II and Class III is 0.05, 0.0 and 0.0 that indicates neural network answers incorrectly for only one Paurashavas of Class I which actually belong to Class II and no misclassification is found for Class II and Class III.

True-neg. ratio (True-Negative Ratio also known as Specificity)

The Paurashavas, which are not classified by the neural network as Class I (they are classified as Class II or Class III), and these Paurashavas actually do not belong to Class I (they belong to Class II or Class III). The neural network answers correctly in these cases. The True-negative ratio for Class I is a ratio of the total number of Class I true-negative classifications to the total number of actual classifications in all classes other than Class I.

True-negative ratio for Class I, Class II and Class III is 0.95, 1.0 and 1.0 that means there is no possibility of having Paurashavas from other class in case of Class II and Class III in the network classifications.

False-neg ratio (False-Negative Ratio)

The Paurashavas, which are not classified by the neural network as Class I (they are classified as Class II or Class III), but these cases actually belong to Class I. The neural network answers incorrectly in these cases: these are misclassifications. The False-negative ratio for Class I is a ratio of the total number of Class I false-negative classifications to the total number of actual Class I classifications.

False-negative ratio for Class I, Class II and Class III is 0.0, 0.1667 and 0.0. Only one Paurashavas of actual Class II are misclassified by neural network but for actual Class I and Class III, neural network does not provide any misclassification.

Sensitivity and Specificity

Sensitivity is the probability of the model to detect the condition when it is present for a particular class. Specificity is the probability that the network model will detect the absence of the condition for a particular class.

Sensitivity and specificity has been applied to an output class of interest. These are ratios, calculated from the number of true-positive and false-positive classifications for the specified class. Sensitivity and specificity are usually expressed as percentages, both ranging from 0% (very bad classifier) to 100% (perfect classifier). The following formula applies to determine sensitivity and specificity of specific class:

Class I sensitivity = (Number of Class I true-positive classifications) / (Total number of actual Class I classifications)*100

Class I specificity = 1 – ((Number of Class I false-positive classifications) / (Total number of cases - Total number of actual Class I classifications))*100

The developed artificial neural network model for classifying Paurashavas provides better result in terms of sensitivity and specificity. Sensitivity for Class I, Class II and Class III is 100%, 83.33% and 100% and specificity for Class I, Class II and Class III is 95%, 100% and 100%. Sensitivity and specificity for each class are equal to 100% or closer to 100% which is an indication of perfect classifier.

The developed artificial neural network model is a better classifier for Paurashavas considering predicting correct classification of Paurashavas as well as sensitivity and specificity.

CHAPTER 6

CONCLUSION

Chapter 6: Conclusion

The study was designed towards understanding the functional classification of Paurashavas based on physical infrastructure and service facilities by applying Artificial Neural Network algorithms. In Bangladesh the classification of Paurashavas into various groups is made on the basis of revenue earned. But from this classification, functional characteristics of the Paurashavas cannot be known because revenue earning cannot and in fact do not reveal the status and level of the essential services. Paurashavas are established to provide municipal services and physical infrastructure to urban dwellers. Naturally the existing classification system failed to provide insight into the nature and extent of various municipal service facilities.

The research explores application of neural networks, a proven, widely used technology to solve complex classification problems for grouping of Paurashavas. In this method the Paurashavas are clustered on the basis of selected variables expressing infrastructure and service facilities, where revenue earning is used as one such factor only. The neural network provides better classification of Paurashava in cases of mean value and value of standard deviation. For all classes of Paurashavas, out of eighteen variables, mean value of most of the variables have been found larger in case of neural network classification than those in the existing classification. The value of standard deviation in case of neural network classification has been found to be smaller in most of the variables, which indicates that the value of the variables for the Paurashavas in different classes is more homogenous and compact in neural network classes in comparison to those in the existing classes.

By comparing weighted average values in percent among various classes, it is found that the average values of variables in case of the three classes of the existing classification vary abruptly and do not significantly express the hierarchy. But in neural network classification, the average values of variables in case of the three classes vary gradually and follow distinct hierarchy as well as distinct dissimilarity which is obvious among classes of different grades. Among selected Paurashavas for classification by using neural network algorithm, significant portion of Paurashavas fall under the lower hierarchy from the corresponding class. The underlying reason for shifting is, these Paurashavas fail to provide adequate utility and community facilities to the urban dwellers and cannot ensure growth and development of non-agricultural income sources like other Paurashavas of same hierarchy.

Finally, in order to understand the basis for the classification from a set of labeled Paurashavas, neural network model has been developed to predict classes for future unlabeled Paurashavas which are not included in the selected Paurashavas for the research. The developed artificial neural network model provides better classification of Paurashavas with respect to sensitivity and specificity. Value of sensitivity and specificity is fairly larger for this model. By this artificial neural network model. Paurashavas can be classified based on available facilities and services provided by the Paurashava authorities that will reveal clear understanding of the status of these services in various Paurashavas. This was an exploratory research providing basis for reclassification of Paurashavas of Bangladesh based on the potentialities of the Paurashavas. In order to understand the underlying reasons for shifting of Paurashavas from corresponding class as well as current investment pattern in the Paurashavas, extensive survey is required that can be further studied.

In order to take any investment decision and development policy in any Paurashava, it is essential to explore its real functional characteristics as may be manifested through available infrastructure and service facilities as well as non-agricultural activities. The classification explored by applying neural network algorithm will provide the essential understanding necessary for adopting planning approaches, which would help to decentralize service facilities and make available improved facilities in the Paurashavas on the basis of their potentialities and also to develop a strategy for balanced development in various Paurashavas.

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APPENDICES

Appendix A

Table A: Data on Selected Variables for the Selected Paurashavas

Name	Age	Wor Pop	Land Use	Pave Rd	Tot Rd	Sur Drn	HH Tap	HH Tube	Epole	ECov	Eline len	Dust	Con Cov	Hos Bed	H care	Mar ket	Rev	Exp
Alamdanga	24	30.51	5.06	79.85	14.11	2.48	1.72	94.32	73	80	3.231	7	87	17	2	3.231	46859	39030
Banaripara	19	44.9	11.25	65.96	37.69	4.81	3.39	90.17	9	60	4.01	16	60	40	1	3.208	84368	54239
Bandarban	24	50 66	34.39	47.83	16.79	5.43	51.53	17.88	61	56	7.299	2	44	15	2	1.752	61799	72350
Barura	14	17.63	13.81	26.92	13.05	0.23	0.9	88.5	58	5	0.227	7	11	8	2	1.361	37692	72350
Bera	21	33 09	28.65	50	15.8	0.9	0 86	85.55	58	50	5.187	7	27	7	2	1.128	70934	72033
Betagi	10	33.73	13.81	50	7.33	0.77	10.39	78.78	58	56	5.187	7	27	33	1	0 667	61799	126168
Bhairab	51	38.35	2.3	80.72	3.49	2.11	2.21	78.34	208	56	5.187	1	47	13	2	1.055	59355	76960
Bhanga	12	33.73	8.24	24.54	10.34	0 04	10.39	78.78	58	56	5.187	7	45	11	1	1.307	22386	17753
Bheramara	26	31.04	14.14	46.13	24 29	6.38	2.6	91.28	10	89	2.121	7	47	9	1	3.182	62982	79486
Bhola	89	41.6	16.52	52.99	12.84	10.55	39.83	55.53	122	75	12.07	6	66	17	4	3.966	39801	147752
Bhuapur	14	17.72	13.7	30.67	29.82	2.39	10.39	78.78	58	56	5.187	20	47	12	1	4.373	45651	56996
Bogra	133	40.07	33.54	68.84	10.76	7.13	12.41	86.21	78	33	1.757	7	64	15	3	0 692	81752	80577
Brahmanbaria	141	34.94	25	49.19	16.66	9.16	11.95	83.46	104	70	5.187	6	69	12	3	2.309	62375	66841
Burhanuddin	11	33.73	13.81	30.77	15.93	0.09	10.39	78.78	67	56	5.187	7	47	18	2	3.676	61799	72350
Chandina	12	33.73	5.28	19.93	28.1	1.46	10.39	78.78	58	56	5.187	3	47	11	1	1.018	36075	11772
Charfassion	19	33.73	8.01	42.86	15.4	5.64	10.39	78.78	52	60	4.801	4	32	12	2	3.201	63546	68179
Charghat	11	33.73	7.5	46.92	15.33	2.09	10.39	78.78	11	56	5.187	7	34	41	2	1.351	13104	5523
Chatmohar	12	33.73	15	60.34	12.87	6.43	10.39	78.78	12	30	2.219	2	53	9	1	0.888	31612	72350
Chhatak	12	33.73	19.23	56.16	13.36	0.27	10.39	78.78	58	56	5.187	3	47	10	1	2.79	52248	8317
Chhengarchar	11	45.15	1.81	8.6	22.2	0.78	10.39	54.58	58	56	5.187	7	47	17	1	0.239	61799	72350
Chuadanga	37	30.44	0.4	21.88	37.57	3.82	23.13	73.49	33	75	17.613	7	47	7	2	1.615	80813	114395
Cox's Bazar	140	50.22	21.29	60.34	5.78	7.57	7.08	83.91	157	86	10.337	5	69	19	2	2.363	145792	168191
Damudya	12	33.73	13.81	28.57	24.95	5.94	10.39	78.78	58	56	5.187	7	47	18	2	2.971	33917	43487
Darsana	18	29.35	33.76	41.1	32.66	1.68	11.06	87.91	13	65	2.632	7	18	10	2	2.872	34140	45125
Daulatkhan	12	21.8	20	53.33	14.11	3.8	10.39	78.78	53	75	6.772	15	29	38	2	0.752	61799	72350

Name	Age	Wor Pop	Land Use	Pave Rd	Tot Rd	Sur Drn	HH Tap	HH Tube	Epole	ECov	Eline len	Dust	Con Cov	Hos Bed	H care	Mar ket	Rev	Exp
Dewanganj	10	22.64	13.37	12.04	20.99	1.17	0.61	94.46	58	56	5.187	7	47	6	2	0.972	61799	72350
Dhanbari	13	33.73	15.47	19.24	17.58	6.7	10.39	78.78	2	10	0.631	3	24	17	2	3.471	39756	75313
Dinajpur	140	36.16	5.75	80.35	9.64	6.67	3.7	90.98	99	90	5.187	13	66	18	5	1.171	41307	77181
Durgapur	15	33.73	10.69	40.46	9.84	1.59	10.39	78.78	11	20	0.901	5	44	30	2	2.403	12915	14115
Faridpur (D)	140	40.12	1.56	79.39	9.12	1.77	26.29	70.71	141	56	11.921	23	93	36	3	5.319	49322	72350
Feni	51	46.72	9.56	76.44	8.33	10.93	30.79	65.42	46	40	1.462	8	42	10	2	0.923	68667	58743
Gaibandha	86	37.06	20.87	66.25	20.38	5.92	22.88	68.58	77	80	14.976	12	71	12	2	2.304	8105	102102
Galachipa	12	33.73	26.47	74.03	14.38	0.93	10.39	78.78	26	35	1.121	7	47	37	1	0.747	106003	15976
Gazipur	23	33.73	25	78.47	21.96	0.32	21.65	63.17	83	23	2.727	27	44	18	3	3.182	76835	149163
Ghatail	11	33.73	16.96	12.87	18.12	3.8	10.39	78.78	58	56	5.187	7	47	24	1	2.429	28818	5004
Ghorashal	11	33.73	34	40.59	7.63	1.47	10.39	78.78	58	56	5.187	7	47	38	2	1.284	2733	2786
Gobindoganj	11	33.73	17.31	15	10.85	3.44	10.39	78.78	67	50	5.187	18	51	18	1	4.34	61799	4630
Gopalpur (D)	35	20.52	16.05	34.93	16.06	1.27	0.38	91.72	12	35	0.641	2	29	5	2	0.962	38910	55775
Gouripur	82	34.57	12.1	86	22.32	6.7	0.92	82.14	16	45	0.893	8	45	22	1	1.785	28923	89378
Gurudashpur	18	24.61	17.5	58.33	7.87	1.8	0.71	90.09	20	40	0.984	1	17	13	1	1.476	59036	72350
Habiganj	128	37.14	18.23	59.42	11.74	4.27	10.99	85.58	58	85	8.175	12	80	25	2	3.19	78289	176030
Hajiganj	24	27.96	14.37	11.98	19.62	2.4	1.09	80.14	21	100	5.187	5	35	8	1	0.959	190327	161365
Ishwardi	35	36.32	3.22	52.58	11.88	0.67	8.81	90.31	82	80	5.999	4	88	4	2	0.735	54454	91134
Ishwarganj	12	33.73	19	20.7	7.11	4.08	10.39	78.78	47	30	0.669	4	22	22	2	1.56	61799	72350
Jamalpur	140	32.4	2.63	62.11	14.15	6.35	7.37	66.76	22	60	2.894	13	53	22	2	0.702	9022	72350
Jessore	145	40.5	4.08	73.63	5.59	6.27	12.94	84.45	82	95	12.293	9	47	12	3	0.738	61799	72350
Jhenaidaha	51	30.85	13.81	29.38	18.43	8.22	14.8	81.25	83	75	3.199	7	52	13	2	1.792	45128	115743
Jibannagar	12	33.73	20	16.22	22.86	1.65	1.06	96.65	58	56	5.187	7	47	13	2	1.646	65708	11582
Joypurhat	34	33.19	17.86	37.3	14.37	10.72	3.92	92.21	108	90	14.296	6	78	16	4	3.263	996737	114908
Kabirhat	12	33.73	2.29	18.7	33	1.61	10.39	78.78	58	25	5.187	4	8	17	1	6.439	61799	5528
Kadam Rasul	16	43.76	42.86	76.29	9.24	1.19	42.79	54.64	19	60	0.286	2	57	17	1	1.334	25349	49762
Kalapara	12	33.73	9.33	62.56	16.94	8.98	10.39	78.78	61	35	4.161	24	45	18	1	4.756	111283	58048
Kalaroa	19	25.88	10.95	32.5	17.15	1.82	1.33	97.7	58	56	5.187	2	30	11	4	2.058	70578	59677
Kalia	33	24.46	0.48	79.53	22.69	2.43	0.08	91.17	22	71	9.242	6	12	5	1	3.235	51481	54487

Name	Age	Wor Pop	Land Use	Pave Rd	Tot Rd	Sur Drn	HH Tap	HH Tube	Epole	ECov	Elline len	Dust	Con Cov	Hos Bed	H care	Mar ket	Rev	Exp
Kaliganj	19	32.11	21.74	59.02	14.31	2.81	3.4	94.13	25	45	1.642	4	48	7	1	3.988	108041	61121
Kendua	11	33.73	13.81	26.83	15.49	3.02	10.39	78.78	58	56	5.187	7	47	17	1	0.567	61799	72350
Khagrachhari	25	45.04	15.73	56.75	18.76	5.41	8.62	72.97	33	40	11.36	7	70	14	2	1.082	109913	138528
Kishoreganj	140	42.17	22.66	74.77	10.66	3.38	10.14	86.57	73	80	6.581	7	29	37	2	5.119	46205	119843
Kotalipara	12	33.73	1.22	47.37	16.31	3.8	10.39	78.78	4	80	1.717	7	47	18	1	0.572	61799	20543
Kulaura	13	33.73	26.67	25.58	32.91	12.5	10.39	78.78	58	56	5.187	7	47	11	1	3.445	22127	25291
Kurigram	37	33.55	18.38	57.47	12.74	11.06	8.46	84.02	34	80	7.322	21	73	21	2	1.025	61799	72350
Laksam	25	33.21	10.56	29.97	13.63	1.2	4.94	90	18	25	2.384	3	54	5	2	3.02	25978	52715
Laksmipur	33	32.11	8.62	49.04	13.39	2.85	1.03	71.32	59	75	6.352	3	67	17	2	1.672	45047	100818
Lalmonirhat	37	33.38	16.67	60.68	11.66	3.82	1.32	86.01	34	60	7.092	11	73	17	3	1.557	6085	74089
Madaripur	134	33.73	30.3	76.23	6.3	1.33	17.61	69.22	151	80	4.893	3	62	10	3	1.198	10273	104156
Madhabpur	12	33.73	25	23.81	6.89	12.53	10.39	78.78	26	35	2.386	7	48	17	1	2.983	9509	92539
Madhupur	14	33.73	9.95	32.23	17.45	0.52	10.39	78.78	12	40	2.684	2	24	6	2	2.064	12825	62254
Magura	37	31.2	12.1	59.6	25.73	1.71	13.47	85	44	75	10.852	7	47	56	6	3.473	56549	237293
Manirampur	12	33.73	1.17	29.44	17.31	3.5	10.39	78.78	25	56	5.187	9	47	17	1	1.757	78645	30232
Matlab	11	33.73	2.5	9.09	10.82	0.82	10.39	78.78	58	56	5.187	7	47	39	1	1.148	2606	72350
Mehendiganj	11	14.03	11.02	25.37	19.52	2.04	10.39	78.78	58	56	5.187	7	47	9	1	0.583	61799	72350
Mirkadeem	14	33.73	40.1	81.62	7.35	3.69	10.39	78.78	58	56	5.187	7	31	17	1	0.807	28056	19681
Mirpur	12	19.61	8.33	37.94	27.79	0.23	0.94	96.8	56	56	5.187	7	14	23	1	3.258	61799	19958
Mohanganj	34	34.42	5.04	87.88	14.41	3.41	0.11	94.83	61	63	6.987	2	35	22	2	3.057	58922	76287
Mongla	34	52.97	18.01	48.75	0.88	0.2	32.64	4.7	169	72	2.199	2	38	5	3	0.33	53025	32392
Munshiganj	37	33.57	1.2	77.42	6.59	3.93	37.99	49.24	165	90	5.317	6	32	11	1	3.19	69858	166764
Mymensingh	140	37.96	1.38	85.02	7.06	3.98	28.23	68.57	105	56	6.28	10	77	30	5	0.442	93327	95899
Nabiganj	12	33.73	11.34	38.4	17.68	2.58	10.39	78.78	58	56	5.187	7	47	16	1	4.053	78026	27635
Nalchity	24	19.47	12.42	57.69	11.72	1.58	0.04	51.86	24	45	1.352	1	16	11	1	1.127	38610	72266
Nalitabari	14	33.73	3.8	55.69	20.19	3.55	10.39	78.78	58	56	5.187	4	49	8	1	3.224	49934	49939
Nandail	12	33.73	13.81	25	12.97	3.8	10.39	78.78	58	25	5.187	7	47	8	1	2.837	38662	72350
Naogaon	46	37.08	6.1	39.1	17	4.7	4.29	89.42	61	30	2.705	5	50	6	3	0.176	65855	71491
Naria	11	33.73	0.63	41.86	17.2	0.08	10.39	78.78	58	56	5.187	7	47	12	1	0.4	17349	18376

Name	Age	Wor Pop	Land Use	Pave Rd	Tot Rd	Sur Drn	HH Tap	HH Tube	Epole	ECov	Ellne len	Dust	Con Cov	Hos Bed	H care	Mar ket	Rev	Exp
Natore	140	38.28	21.96	59.97	11.14	7.09	9.29	89.35	153	66	8.077	6	70	16	2	2.951	38942	97215
Nawabganj	106	27.36	2.44	49.37	8.56	4.18	7.67	81.39	53	30	8.568	5	44	9	3	1.263	74863	57310
Nilphamari	37	30.97	27.32	50.37	15.77	8.27	1.9	53.67	84	62	5.905	7	62	30	2	1.476	95388	104602
Pabna	133	38.6	33.82	57.14	7.73	5.93	15.82	79.9	167	65	5.524	28	74	49	4	2.578	77584	107351
Paikgachha	12	33.73	15.94	37.25	22.58	1.74	10.39	98.01	6	47	4.132	4	47	30	1	14.756	945	72350
Panchagar	24	37.88	13.49	44.01	14.44	15.96	3.55	56.52	65	79	10.363	16	47	21	2	1.658	82554	95177
Panchbibi	11	33.73	44.7	6.48	12.36	4.51	10.39	78.78	58	56	5.187	7	25	17	1	2.003	61799	72350
Pangsha	19	26.9	0.88	66.99	14.04	2.54	0.56	93.79	19	15	1.908	3	11	14	1	1.908	47456	73883
Parbatipur	37	35.73	26.85	65.31	20.24	12.2	1.04	95.71	51	85	5.187	24	89	5	2	2.809	84707	85919
Patgram	10	51.25	0.61	28.06	17.2	2.97	10.39	42.46	17	33	3.96	20	28	15	1	1.98	61799	72350
Patiya	19	35.22	13.81	88.74	11.46	2.38	0.81	95.51	26	60	2.816	6	66	7	5	1.173	94563	80465
Patuakhali	117	39.17	9.62	83.87	24.7	2.71	51.56	45.83	71	85	10.36	3	96	45	6	2.391	16396	145641
Pirganj	20	33.73	15.34	33.92	29.9	2.95	1.33	78.24	6	15	0.952	5	38	15	1	2.38	762	72350
Pirojpur	124	31.83	7.19	50.84	17.33	1.57	43.31	50.73	184	80	10.648	3	49	20	5	1.863	64753	92691
Ramganj	18	23.6	11.73	41.59	23.15	0.82	0.31	88.21	58	56	5.187	2	26	20	4	2.663	27770	72350
Raozan	11	33.73	13.81	100	7.29	3.8	10.39	78.78	3	56	5.187	3	47	17	3	1.657	61799	12069
Rohanpur	24	33.73	13.81	25.21	11.23	1.6	10.39	78.78	12	48	1.06	1	24	7	1	2.333	47750	63083
Saidpur	51	36.29	13.81	81.82	7.38	13.41	7.16	76.41	57	80	10.309	3	84	13	4	0.168	55527	77067
Santahar	21	35.69	13.81	32.06	14.49	6.59	2.22	97.14	58	56	5.187	7	47	3	1	1.227	62383	102024
Santhia	12	33.73	10	38.7	14.92	3.92	10.39	78.78	58	80	5.187	7	14	8	1	1.829	61799	5218
Sariakandi	10	33.73	7.25	39.13	20.91	1.82	10.39	78.78	58	20	1.818	3	18	23	2	1.818	61799	72350
Shaestaganj	11	43.26	18.75	53.05	21.44	5.99	10.39	78.78	12	25	0.503	10	57	17	1	2.268	43536	9702
Shahjadpur	20	32.71	8.24	29.89	5.97	2.55	10.39	78.78	61	20	4.026	4	68	3	2	4.428	49858	58641
Shahrasti	11	33.73	5.38	30.43	20.95	5.83	10.39	78.78	130	56	7.287	8	46	11	2	2.55	61799	72350
Shailkupa	17	33.73	14.34	65.3	25.38	2.15	0.11	95.57	14	45	2.196	3	24	7	1	2.44	61799	72350
Shariatpur	24	25.28	20.2	55	19.11	2.48	0.54	81.47	28	50	1.911	4	50	38	6	2.102	21431	55676
Sharishabari	19	28.01	7.8	70.97	8.02	1.36	0.28	92.72	33	— 45	2.718	— 1	- 28	4	1	0.906	32215	34676
Sherpur (D)	140	33.95	12.2	72.74	11.81	3.67	1.08	94.55	42	50	3.091	3	45	22	2	3.22	69771	69656
Shibchar	12	33.73	0.69	38.34	38.95	1.95	10.39	78.78	19	25	5.016	22	50	20	2	4.458	76923	142349

Name	Age	Wor Pop	Land Use	Pave Rd	Tot Rd	Sur Drn	HH Tap	HH Tube	Epole	ECov	Eline len	Dust	Con Cov	Hos Bed	H care	Mar ket	Rev	Exp
Shibganj	17	23.36	8.97	36.6	20.72	3.87	10.39	78.78	8	21	0.43	5	53	13	1	1.291	54537	60037
Shitakundu	11	33.73	13.81	76.63	8.84	0.62	10.39	78.78	58	56	5.187	7	47	6	2	1.315	40631	40587
Singra	10	23.29	13.81	28	6.57	0.78	10.39	78.78	58	56	5.187	3	53	8	1	6.046	61799	72350
Sirajganj	140	40.09	1.05	55.3	8.37	2.35	2.56	89.66	57	70	1.269	8	63	24	3	0.888	65928	83313
Sunamganj	90	38.52	11.73	60.42	24.27	4.2	9.58	88.27	113	56	10.54	2	47	30	3	8.131	137544	288223
Swarupkathi	11	34.1	3.61	40.12	8.53	0.08	10.39	78.78	58	56	5.187	2	41	26	1	1.532	61799	72350
Tangail	122	35.12	1.83	26.58	17.56	2.42	17.67	70.73	68	60	10.649	12	52	7	2	1.028	61724	71002
Tanore	14	33.73	12.03	23	15.91	6.21	10.39	78.78	58	56	5.187	7	47	21	1	3.224	49188	32204
Thakurgaon	51	37.68	12.5	63.67	13.8	4.25	3.98	89.89	122	90	10.308	9	47	23	1	1.406	26286	138787
Trishal	11	28.72	16.46	34.19	21.75	1.95	10.39	78.78	58	56	5.187	7	47	17	1	2.228	61799	72350
Tungipara	12	33.73	13.81	72.22	26.75	2.23	10.39	78.78	58	56	5.944	11	47	61	1	1.486	9299	72350
Ulipur	11	33.73	20.48	9.39	9.73	0.56	10.39	78.78	58	56	5.187	1	14	22	4	0.292	22518	2617
Ullahpara	15	33.73	18.11	25.25	18.26	1.99	10.39	78.78	58	56	5.187	4	22	7	2	4.058	55646	57083

Source: Paurashava Statistical Year Book, 1998-1999

Appendix B

Table B: Comparison between Existing Classification and Neural Network Classification of Paurashavas

Name of Paurashavas	Existing Classification	Neural Network Classification
Alamdanga	B	II
Banaripara	C	II
Bandarban	A	II
Barura	C	III
Bera	B	III
Betagi	C	III
Bhairab	A	II
Bhanga	C	III
Bheramara	C	III
Bhola	A	I
Bhuapur	C	III
Bogra	A	I
Brahmanbaria	A	I
Burhanuddin	C	III
Chandina	C	III
Charfassion	C	III
Charghat	C	III
Chatmohar	C	III
Chhatak	C	III
Chhengarchar	C	III
Chuadanga	A	III
Cox's Bazar	A	I
Damudya	C	III
Darsana	C	III
Daulatkhan	C	II
Dewanganj	C	III
Dhanbari	C	III
Dinajpur	A	I
Durgapur	C	III
Faridpur	A	I
Feni	A	II
Gaibandha	B	I
Galachipa	C	II
Gazipur	A	II
Ghatail	C	III
Ghorashal	C	II
Gobindoganj	C	III
Gopalpur	B	III
Gouripur	B	II
Gurudashpur	B	III

Name of Paurashavas	Existing Classification	Neural Network Classification
Habiganj	A	I
Hajiganj	B	III
Ishwardi	A	II
Ishwarganj	C	III
Jamalpur	A	I
Jessore	A	I
Jhenaidaha	A	II
Jibannagar	C	III
Joypurhat	A	I
Kabirhat	C	III
Kadam Rasul	B	II
Kalapara	C	II
Kalaroa	C	III
Kalia	C	III
Kaliganj	B	III
Kendua	C	III
Khagrachhari	B	II
Kishoreganj	A	I
Kotalipara	C	III
Kulaura	C	III
Kurigram	B	II
Laksam	B	III
Laksmipur	A	II
Lalmonirhat	B	II
Madaripur	A	I
Madhabpur	C	III
Madhupur	C	III
Magura	A	II
Manirampur	C	III
Matlab	C	III
Mehendiganj	C	III
Mirkadeem	C	II
Mirpur	C	III
Mohanganj	B	II
Mongla	B	II
Munshiganj	A	II
Mymensingh	A	I
Nabiganj	C	III
Nalchity	B	III
Nalitabari	C	III
Nandail	C	III
Naogaon	A	III
Naria	C	III
Natore	A	I
Nawabganj	A	I

Name of Paurashavas	Existing Classification	Neural Network Classification
Nilphamari	B	II
Pabna	A	I
Paikgachha	C	III
Panchagar	B	II
Panchbibi	C	III
Pangsha	C	III
Parbatipur	B	II
Patgram	C	III
Patiya	B	II
Patuakhali	A	I
Pirganj	C	III
Pirojpur	A	I
Ramganj	C	III
Raozan	C	II
Rohanpur	C	III
Saidpur	A	I
Santahar	C	III
Santhia	C	III
Sariakandi	C	III
Shaestaganj	C	III
Shahjadpur	C	III
Shahrasti	C	III
Shailkupa	C	III
Shariatpur	B	II
Sharishabari	C	III
Sherpur	A	I
Shibchar	B	III
Shibganj	C	III
Shitakundu	C	II
Singra	C	III
Sirajganj	A	I
Sunamganj	A	I
Swarupkathi	C	III
Tangail	A	I
Tanore	C	III
Thakurgaon	A	II
Trishal	C	III
Tungipara	C	II
Ulipur	C	III
Ullahpara	C	III

Appendix C

Table C: Weighted Average (%) of Different Classes of Paurashavas

Variables	Existing Classification			Classification by Neural Network		
	A	B	C	I	II	III
Age	138 60%	-19.75%	-64.95%	206.63%	-25.52%	-60.04%
WorPop	13.82%	2.53%	-7.93%	10.74%	6.30%	-6.66%
LandUse	-7.82%	24.54%	-3.91%	1.77%	22.37%	-10.99%
PaveRd	26.59%	19.28%	-19.93%	31.86%	36.23%	-27.88%
TotRd	-16.11%	-2.21%	9.01%	-23.28%	-8.67%	12.12%
SurDrn	42.23%	22.97%	-29.17%	45.22%	20.18%	-25.09%
HHTap	57.31%	-34.73%	-18.26%	52.85%	13.48%	-24.63%
HHTube	-4.05%	-2.64%	2.94%	-1.65%	-6.04%	3.37%
Epole	62 62%	-24.47%	-24.32%	67.69%	9.01%	-27.73%
ECov	21.08%	4.43%	-12.28%	25.39%	11.02%	-13.94%
Elinclen	46.26%	-7.88%	-21.26%	57.35%	0.62%	-20.24%
Dust	9.81%	8.99%	-7.96%	17.72%	24.04%	-17.31%
ConCov	31.24%	14.11%	-20.65%	38.06%	13.84%	-19.66%
HosBed	13.97%	-15.68%	-2.12%	23.05%	23.05%	-18.71%
Hcare	48.25%	7.91%	-27.39%	61.71%	10.26%	-26 22%
Market	-2.63%	-23.72%	9.03%	5.20%	-20.34%	7 62%
Rev	42.84%	1.97%	-22.69%	60.95%	-6.98%	-17.96%
Exp	52.10%	12.19%	-30.76%	47.43%	10.12%	-21.19%