1.1 INTRODUCTION

Remote Sensing classification typically involves the use of spectral samples at a fixed spatial resolution to discriminate a fixed set of classes whose spectral and spatial characteristics are variable. According to the progress of space technology, remote sensing has become important in pattern classification from viewpoint of global environmental problems. But pattern recognition methods for remote sensing are mainly based on statistical methods, such as maximum likelihood or Bayesian methods. Since the mid 1980's there has been a steady growth in the number of applications of artificial neural network algorithms in a wide range of scientific disciplines. The use of neural networks in remote sensing is relatively new. However during the last few years the number of reported applications has been steadily increasing. Benediktsson et al., (1993) Paola and Schowengerdt (1995) and Bischof et al., (1998) have applied neural network for classifying the satellite image. The majority of applications have used the multi-layer perceptron neural network trained with the back-propagation algorithm although applications employing the self-organising topological maps and LVQ methods have also been reported. The analysis has been carried out on a variety of remotely-sensed data including optical high (Landsat, SPOT) and low (NOAA-AVHRR) resolution multi-spectral imagery, data from Imaging Spectrometers (AVIRIS), and Synthetic Aperture Radar (SAR) data (ERS-1). Although early experiments made use of single source data, more recent work has demonstrated the
flexibility of neural networks for fusion of multi-source data for improved land cover classification.

1.2 NEED FOR THE STUDY

Modern remote sensing satellites generate multispectral data from a variety of sensors. Timely analysis of this plethora of data already presents a formidable challenge. As the spatial, spectral and temporal resolution increase, the need for advanced and efficient techniques escalates. Development of advanced techniques for improving remote sensing image classification accuracy is essential for deriving reliable land cover information for both cultural and natural resources applications. A distribution free and measurement scale free classification technique is desirable for processing spatial data. Artificial neural networks are among the optimal Artificial Intelligence tools for this type of applications.

1.3 BACKGROUND

1.3.1 Artificial Intelligence

Artificial Intelligence is machine emulation of the human thinking processes (Bose, 1994). The term Artificial Intelligence is computer process that attempts to emulate the human thought processes that are associated with activities that require the use of intelligence. Human brain is the most complex machine on earth. It is possible to generate such intelligence, or at least a part of it, artificially with help of a computer so that it can solve our complex problems, which are difficult to solve in traditional way. In human visual image interpretation, the criteria used for classification can be broadly defined by the tone or color, size, shape, shadow, pattern, texture, and spatial relationships of the ground targets. An interpreter’s knowledge, experience, and familiarity with a study area also contribute to the classification process. The powerful capabilities for knowledge acquisition, recall, synthesis, and problem solving of
the human brain have inspired scientists from different disciplines to attempt to model its operations. Based on the biological theory of human brain, artificial neural networks are models that attempt to parallel and simulate the functionality and decision-making processes of the human brain. In general, a neural network is referred to as a mathematical model of theorized mind and brain activity (Civco, 1994).

Neural Network or Artificial Neural Network (ANN), as the name indicates is the interconnection of artificial neurons that tends to simulate the nervous system of a human brain. It is also defined in literature as a neuro computer or a connection system (Freeman et al., 1991).

The human nervous system consists of cells called neurons. There are hundreds of billions of neurons, each connected to hundreds or thousands of other neurons. Each neuron is capable of receiving, processing and transmitting electrochemical signals over the neural pathways that comprise the brain’s communication system. The neurons consist of four basic parts: the cell body, synapse, axon and dendrite. Dendrites are the branch like structures that provide the input to a cell body. Dendrites receive signals from other neurons at connection points called synapses. On the receiving side of a synapse these inputs are connected to the cell body. The cell body essentially sums the membrane potentials provided by the dendrites. When the cumulative excitation in the cell body exceeds the threshold, the cell fires, sending a signal down the axon to another neuron. ANNs consists of a large number of neurons or simple processing units, also referred to as neurodes. An artificial neuron mimics the characteristics of the biological neuron. Here, a set of inputs is applied, each representing an output of another neuron. Each input is multiplied by a corresponding weight, analogous to synaptic strengths. The weighted inputs are summed to determine the activation level of the neuron. The connection strengths or the weights represent the knowledge in the system. Information processing takes place through the interaction among these units.
Neural elements of a human brain have a computing speed of a few milliseconds, whereas the computing speed of electronic circuits is of the order of microseconds. In spite of its very low processing speed, the human brain resolves vision and language problems much faster than the fastest computers. ANN models mimic the human brain. They provide a computing architecture that is radically different from the computers that are widely used today and they are massively parallel systems.

Artificial Neural Networks have been used to model the human vision system (Kulkarni, 1994). They are biologically inspired and contain a large number of simple processing elements that perform in a manner that is analogous to the most elementary functions of neurons. ANN models learn by experience, generalize from previous experiences to new ones, and can make decisions. ANN models are preferred for image understanding tasks because of their parallel processing capabilities as well as learning and decision making abilities. Image understanding deals with recognition of various objects in a scene (Kulkarni, 1994). It includes image processing and pattern recognition. Often, the ultimate aim in developing an image understanding system is to perform tasks that are normally performed by a human vision system.

The artificial neuron (simply neuron) is also called a Processing Element (PE). The ANN has input layer, hidden layer and output layer.

1.3.2 Satellite Remote Sensing

Remote Sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation (Lillesand, 1994). According to Schowengerdt (1997), Remote Sensing is the measurement of object properties on the earth’s surface using
data acquired from aircraft and satellites. It is therefore an attempt to measure something at a distance, rather than in situ.

Remote Sensing data can consist of discrete and point measurements over a two dimensional spatial grid, i.e. images. Remote Sensing systems, particularly those provided on satellite, provide a repetitive and consistent view of the earth that is invaluable to monitoring the earth system and effect of human activities on the earth.

The remotely collected data can be of many forms, including variations in force distribution, acoustic wave distribution, or electromagnetic energy distributions. Human eyes acquire data on variations in electromagnetic energy distributions. The electromagnetic energy sensors are currently being operated from airborne and space borne platforms to assist in inventorying, Mapping and monitoring earth resources (Hord, 1982). These sensors acquire data on the way various earth surface features emit and reflect electromagnetic energy, and these data are analyzed to provide information about the resources under investigation. The two basic process involved are data acquisition and data analysis. The elements of the data acquisition process are energy sources, propagation of energy through the atmosphere, energy interaction with earth surface features, retransmission of energy through the atmosphere, airborne and space borne sensors, resulting in the generation of sensor data in pictorial and digital form. Hence the sensors are used to record variations in the way earth surface features reflect and emit electromagnetic energy.

The data analysis process involves examining the data using various viewing and interpretation devices to analysis pictorial data or a computer to analyze digital sensor data. Reference data about the type, extent, location and condition of the various resources are collected. The acquisition of reference data involves collecting measurements or observations about the objects, areas or phenomena that are being sensed remotely. These data can take on any of a
number of different forms and may be derived from a number of sources. This may stem from a field check on the identity, extent, and condition of agricultural crops, land uses, tree species or water pollution problems. The geographic positions at which such field measurements are made are often noted on a map base to facilitate their location in a corresponding remote sensing image. Increasingly, Global Positioning System (GPS) receivers and automated field recorders are being used for such purpose. Reference data are often referred by the term ground truth. Ground truth may be collected in the air, in the form of detailed aerial photographs used as a reference data when analyzing the high altitude satellite image. Similarly, the ground truth will actually be water truth if water features are studied. Reference data might be used to serve any or all of the following purpose.

a) To aid in the analysis and interpretation of remotely sensed data.

b) To calibrate a sensor

c) To verify information extracted from remote sensing data.

Hence reference data must often be collected in accordance with the principles of statistical design. This information is then compiled, generally in the form of hard copy maps and tables or as computer files.

To meet the needs of different data users, there are many remote sensing systems, offering a wide range of spatial, spectral and temporal parameters. Some users may require frequent, repetitive coverage with relatively low spatial resolution (meteorology). Others may desire the highest possible spatial resolution with repeat coverage only infrequently (mapping): While some users need both high spatial resolution and frequent coverage, plus rapid image delivery and validate large computer models that attempt to simulate and predict the earth’s environment. In this case, high spatial resolution may be undesirable because of computational requirements, but accurate and consistent sensor calibration over time and space is essential.
1.3.3 Satellite Image Processing

Remotely sensed data of Earth may be analyzed to extract useful thematic information. Here the data are transformed into information and multispectral classification is one of the most often used methods of information extraction. Classification algorithms may be grouped into one of two types: parametric and nonparametric (Schowengerdt, 1997). Parametric algorithms assume a particular class statistical distribution, commonly the normal distribution, and require estimates of the distribution parameters, such as mean vector and covariance matrix, for classification. Nonparametric algorithms make no assumptions about the probability distribution and are often considered robust because they may work well for a wide variety of class distribution, as long as the class signatures are reasonably distinct.

The parametric classification can be done in two ways such as Supervised and Unsupervised classification approaches. In a supervised classification, the identity and location of some of the land cover types, such as urban, agriculture and wetland are known a priori through a combination of fieldwork, analysis of aerial photographs and personal experience. The specific site in the remotely sensed data can be located which represents the homogeneous examples of known land-cover types. These areas are commonly referred to as training sites because the spectral characteristics of these known areas are used to train the classification algorithm for eventual land cover mapping of the remainder of the image. Multivariate statistical parameters (means, standard deviations, covariance matrices, correlation matrices) are calculated for each training site. In an Unsupervised classification, the identities of land cover types to be specified as classes within a scene are not generally known a priori because ground reference information is lacking or the surface features within the scene are not well defined. The computer is required to group pixels with similar spectral characteristics into unique clusters according
to some statistically determined criteria. Then it will be combined and labeled into information classes.

Significant advances have been made in digital Image processing of remotely sensed data for scientific visualization (Jensen, 1996). Enhancing the image, classifying the data into land use and land cover, and identifying change between dates of imagery are now performed routinely with reasonable precision. Interestingly, most of the computer assisted image processing has involved the use of only a few of the basic elements of image interpretation. In fact, the overwhelming majority of all digital image analysis appears to be dependent primarily on just the tone and color of individual pixels in the scene using fundamental statistical pattern recognition techniques. Various techniques have been used to measure and incorporate additional elements of image interpretation into the image analysis process. Numerous studies have synthesized texture information from the spectral data in the imagery. Also, several attempts on contextual classification make use of neighboring pixel values, Thus incorporating some level of association information. Even though the computer assisted use of several of these elements of image interpretation shows promise, the majority of the image processing is still based on the statistical pattern recognition analysis of multispectral tone and color. In any real image adjacent pixels are related or correlated, both because imaging sensors acquire significant portions of energy from adjacent pixels and because ground cover types generally occur over a region that is large compared with the size of a pixel (Richards, 1993). In an agricultural area, for example, if a particular image pixel represents paddy it is highly likely that its neighbouring pixel will also be paddy. The degree to which adjacent pixels are strongly correlated will depend on the spatial resolution and the scale of natural and cultural regions on the earth surface. The contextual classifier uses both spectral as well as spatial information for the classification of image.
Kartikeyan et al., (1994) used contextual techniques for classification of high and low-resolution remote sensing data. They proposed two contextual classification methods. One is for the low resolution (LISS I) and the other is for the high resolution (LISS II) image and compared the results from these two methods with Gaussian Maximum Likelihood (GML) classifier. The first contextual method consistently improved the classification accuracies over GML for low-resolution data in all the class, and second contextual method improved classification accuracies for high-resolution data over GML. A comparison of computation times for the two contextual methods with GML shows that the first method took thrice, and the second method took about forty times computation as compared to GML. Khazenie et al., (1990) developed a method for contextual classification, which considers both spatial and temporal correlation for process, which satisfy second order stationary conditions.

Human beings are very successful in visually interpreting images because they focus their real world knowledge about the study area and their 20 to 30 years of visual processing experience to the task. It is difficult to make a computer to understand and use the heuristic rules of thumb and knowledge that a human expert uses when interpreting an image. There has been considerable success recently in the use of Artificial Intelligence (AI), to try and make computers do things that, at moment, people do better. One area of AI that has great potential in remote sensing image analysis is the use of Expert systems. Expert systems can be used to interpret an image and place all the information contained within an image in its proper context with other ancillary data and extract more valuable information. Novices to more accurately interpret remotely sensed image might use the collateral data and rules specified by an expert. Recently, neural network have been used to analyze the remotely sensed data. A hybrid of Neural Network and expert system has been developed for the classification of spatial data. Skidmore et al., (1993) developed a hybrid of neural network and expert system to map land cover such as forest soil or
vegetation overstorey from digital spatial data. This method exhibits the inherent advantages of both neural network and expert system models. The prior knowledge may be hardwired into the probability matrix and used to decide the most likely class to represent the cell. Solaiman et al., (1999) also used neural network and multi expert approach in classifying the Landsat images.

Recently, there has been a resurgence of research in neural networks. Neural network models have an advantage over the statistical methods in that they are distribution free and no prior knowledge is needed about the statistical distribution of the classes in the data sources in order to apply these methods for classification. Paola and Schowengerdt (1995) carried out detailed comparison between maximum likelihood and back propagation trained neural networks for the classification of urban land use from Landsat TM images. Although the overall classification accuracy figures appear to be similar in many cases the authors are also considered 2-dimensional plots of the decision surfaces of both classification methods to explain the differences between the two classifiers in the classification maps.

The maximum likelihood algorithm based on Gaussian probability distribution functions is considered to be the best classifier in the sense of obtaining optimal classification rate. However, the application, of neural network to the classification of satellite image is increasingly emerging without any assumption about the probabilistic model to the made and the network are capable of forming highly non linear decision boundaries. Frizzelle et al., (2001) compared the maximum likelihood and Artificial Neural Network classifiers in mapping continuous distribution of Land cover. They have selected 39 test regions within a heterogeneous study area in southern California. The neural network models consistently produced stronger correlation between output values for a given class and proportions of that class
for all test regions combined. The neural network classifier outperformed the maximum likelihood classifier for both hard and continuous classification.

The present research has been carried out in classifying three study areas (Urban area, Non-urban area and Urban and Non-urban areas on different sensors) using Artificial Neural Network, Maximum Likelihood, Minimum Distance and Contextual Classifiers.

1.4 OBJECTIVES

The objectives of the present study are as follows

1. To identify, classify and quantify the different land uses in the Satellite images pertaining to Urban and Non Urban areas using different algorithms.

2. To identify, classify and quantify mixed land use (both urban and non urban) of Satellite image pertaining to different sensors (IRS 1C LISS III and SPOT HRV (MLA)) using different algorithms.

3. To evaluate the training and classification time of different algorithms.

4. To assess the accuracy of the classification.

1.5 REVIEW OF LITERATURE

Solaiman et al., (2001) compared the conventional and neural network classification of multispectral data. The authors obtained main result in this study is that the application of topological map based neural networks to classify the intensity vectors issued from agricultural classes are more suited than other neural network methods. They obtained results very close to those of the maximum likelihood classifier. Pandey et al., (1997) demonstrated the usage of neural network with considerable reduction in training size, large
spatial extensions and fine-tuning the classification. The illustration has been made through two case studies vz landuse/landcover classification of Delhi ridge and species classification of floral resources in Shimla and Chopal regions. They compared the ANN results with MLC and minimum distance classifiers.

Rangasaneri et al., (1998) used multiplayer perceptron (MLP) neural network using the back propagation algorithm for classification of multispectral images. The authors used JER-1/OPS image for comparing with the gaussian maximum likelihood. Fauzi et al., (2001) compared maximum likelihood and neural network classifiers to detect tropical rain logged – over forest in Indonesia. The authors found the use of NN classifier is found to improve the accuracy of classification result as compared to maximum likelihood classifier. Merenyi et al., (1996) compared Neural Network and conventional classifier in classifying the hyper spectral imagery. They concluded that the Artificial Neural Network (ANN) produces comparable or better results than the classical methods in terms of map accuracy. Schwaiger et al., (1995) used neural network to classify Landsat TM data and arrived overall accuracy of 73 percent. Cheung Wai Chan et al., (2002) studied the performance of difference machine learning algorithms for detecting nature of change and compared. They used Multi-layer perceptron (MLP), Learning Vector Quantization (LVQ), Decision Tree Classifiers (DTC) and Maximum Likelihood Classifier (MLC) compare to conventional post classification comparison methods; LVQ and DTC did better in terms of overall accuracy.

Attempts to map land use directly from higher spatial resolution satellite data with conventional computer classification techniques have proven to be ineffective (Peng Gong, 1998). This is due to two facts. First, landuse is a cultural concept. What we see on remote sensing imagery is only the physical evidence of landuse as represented by combinations of landcover types. Second, conventional classifiers employ only spectral information on single pixel basis.
A large amount of spatial information is thus ignored. He developed three contextual classification procedures to obtain land use information. In the first procedure, multispectral data and edge density image were used to generate land cover information using the supervised Maximum likelihood classifier. In the second classification procedure, the number of grey-level vectors in multispectral space was reduced using a new data reduction algorithm through rotating multispectral space into eigen space. The third procedure involved a new clustering algorithm based upon grey-level vector reduction.

Benediktsson et al., (1993) used a three-layer network and a conjugate-gradient multi-layer network for the classification of multi-source data, namely, Landsat MSS and ancillary topographic data such as elevation slope and aspect, into ten ground-cover classes. They compared their results to statistical techniques and they showed that if the neural networks are trained with representative training samples they could do better than statistical methods. On the other hand, neural networks were inferior to statistical techniques in the classification of very high dimensional simulated High Resolution Imaging Spectrometer (HIRIS) data. However, the HIRIS data were simulated to be Gaussian, which gives an advantage to the statistical methods. The authors also used an alternative data representation for the inputs to the neural networks. In most cases the individual pixel values, appropriately scaled, are used as inputs to the network. The input vectors are binary or Gray coded. They argue that by using binary input data extra dimensions are added to the input, which can help in discriminating the data. A similar encoding for the input data has been employed by Heerman and Khazenie (1992). They used a three-layer network to classify both simulated data and two dates of Landsat TM scenes. To assess the accuracy of the network, it was compared to an unsupervised clustering algorithm, a piecewise linear classifier and a statistical contextual technique. Benediktsson et al., (1997) proposed hybrid statistical/
neural network consensus theory which has potential to apply successfully for many difficult classification and data problems.

Bischof et al., (1992) used another kind of coding the input data, for the classification of Landsat TM data into 4 land cover classes. They applied coarse coding which may be considered as a kind of interpolation. The overall classification accuracy achieved by the neural network was better than that achieved by the maximum likelihood. However the maximum likelihood was able to separate better one category, the agricultural class. The authors also examined the integration of textural features and multi-spectral data into the neural network classifier. With the added texture the network was able to classify the agricultural area more accurately resulting in a greater overall accuracy. Post-classification smoothing was also performed using a two layer network.

Hara et al., (1994) classified fully polarimetric SAR images using first an unsupervised neural network, Learning Vector quantisation (LVQ), to automatically classify the imagery and then an iterative algorithm where the SAR image is re-classified using the maximum likelihood classifier to improve the performance. Salu et al., (1993) used a different neural network model called the binary diamond neural network, for the classification of multi-spectral image data. They compared the performance of the binary diamond with that of a nearest-neighbour classifier and a neural network trained with the back-propagation. According to their results the binary diamond performed better than the other two methods. Moreover the nearest-neighbour was better than the back-propagation network.

Arai (1992) proposed a methodology for purification of training samples for pixel-wise Maximum Likelihood Classification. In this method, pixels, which show comparatively high local spectral variability as well as spectrally separable classes, are removed from the preliminary designated
training samples. He used Thematic Mapper data and this showed the improvement in the separability of 3.78 times in terms of divergence between a specific class pair: goodness of fit to Gaussian can be improved 0.14 times in terms of chi-square: 11.9 percent improvement of weighted mean percentage classification accuracy can be achieved: and most importantly, a 20.6 percent improvement of probability of correct classification can be achieved for a specific class.

Abuelgasim et al., (1999) developed Change Detection Adaptive Fuzzy (CDAF) neural network, which learns fuzzy membership functions for each land cover class present at the first image date based on a sample of the image data. An image from later date is then classified using this network to recognize change among familiar classes as well as change to unfamiliar land covers classes. The newly developed neural network approach resulted in an accuracy of 86% compared to an accuracy of 70% for K-means algorithm and 65% for MLC approach.

Artificial Neural Network (ANN) has gained increasing popularity as an alternative to statistical methods for classification of Remote sensing data (Schwaiger et al., 1995). They used adapted neural network for land cover classification of Landsat images. Artificial Neural Network classifiers have been consistently and convincingly shown to outperform traditional ML based techniques in the area of Remote Sensing (Mokken, 1995). Muttiah et al., quoted neural network have found many interesting uses in remote sensing because they allow integration of remote sensing and other complementary land use information in image processing classification. They also said classical classifiers, such as maximum likelihood and nearest neighbor classifiers have been primarily applicable with only satellite image band information. Their network converged to a mean square error of 1.30 after 4000 iterations.
Vassilas et al., (1995) used neural networks for fast and efficient classification of multispectral remote sensing data. They used two different ANN models for data classification, namely, a single layered network using the learning vector quantization (LVQ) algorithms and a multilayered feed forward network with an error back-propagation learning algorithm enhanced with constrained optimization techniques. They found good performance of the ANN classifiers in terms of training and classification CPU time.

Liu (2000) presented a new method based on artificial neural network using Levenburg Marquart algorithm to detect the change from non-urban land use to urban land use. Compared to post classification comparison, ANN was 40% more accurate when Kappa coefficient was used to measure change detection accuracy. For comparison purposes the author used maximum likelihood as the classifier to perform post classification.

It has been observed that the land use classes on high-resolution imagery are highly deviated from normal distributions (Shaban et al., 1997). They studied the behavior of non-parametric classifier (BPN of ANN) technique for classification of an urban area, which is dominated by non-normal land use classes using spectral and textural features. They have studied the three multispectral (XS) bands of SPOT satellite image of Lucknow city. For ANN based classifications, adding single texture feature to spectral features improves classification accuracy over classification with pure spectral features for most of the texture features used. But adding the best two texture features does not improve classification accuracy over using single texture.

Solaiman et al., (1994) used neural network and multi-experts approach to classify the multispectral LANDSAT images. Their results were very promising in terms of edge preservation. Reich et al., (1996) reported that coherence information could improve classification accuracy especially in all cases where no data from optical sensors are available. They used ERS1/ERS2
SAR data. Gopal et al., (1996) used ANN techniques to find out the change in the forest area. They reported that the neural network classifiers outperform the conventional classifiers mainly due to their lack of assumptions about normality in datasets, considerable ease in using multidomain datasets and perhaps in capturing some of the inherent nonlinearity in such data.

Trung (1996) used layered neural network and maximum likelihood algorithms for classification of remotely sensed images. The proposed LNN based classification system provides a flexible and convenient tool for the classification of remotely sensed images and assessing its classification accuracy in the practical applications.

Jhung et al., (1996) used bayesian contextual classification based on modified M-Estimates and Markov random fields. The common non-contextual classifier is the conventional pixel-wise spectral classifier which relies on the first and second order statistics (mean and covariance estimates) derived from the training samples of each information class. The experimental results show that the suggested scheme outperform conventional noncontextual classifiers as well as contextual classifiers which are based on least squares estimates or other spatial interaction models.

Huunema et al., (1996) classified the multi sensor data using a combination of image analysis techniques such as maximum likelihood and neural network classifiers. This analysis resulted reduce in processing time while, at the same time, reinforcing the performance of both classifiers. Jia et al., (1994) used efficient maximum likelihood classification for imaging spectrometer data sets.

Baraldi et al., (1995) proposed ANN model called Simplified Adaptive Resonance Theory Neural Network (SARTNN) which performs unsupervised recognition of categories from arbitrary sequences of multivalued
input patterns. They tested the performance of SARTNN as a satellite image-clustering algorithm. In comparison with classical clustering algorithms like ISODATA, the implemented system gives good results in terms of ease of use, parameter robustness and computation time.

Tzeng et al., (1994) proposed a dynamic learning Kalman filter algorithm based on the Polynomial Basis Function (PBF) modeled neural network that is a modified multilayer perceptrons (MLP) network for remote sensing applications. Results indicates the use of Kalman filtering algorithm not only substantially increases the convergence rate in the learning stage, but also enhances the separability for highly nonlinear boundaries problem, as compared to BP algorithm.

The conventional method for classification of satellite imagery is based on Bayes' theorem (Shimizu, 1998). He used Fuzzy classification of satellite imagery by Neural Networks. By defining the membership function of class fuzzy set on the least squares criteria from the training data, I/O system equivalent to this function can be realized with back propagation algorithm of neural network. He evaluated the fuzzy classification in comparison with the conventional supervised classification. The fuzzy classification method is able to provide a land cover classification superior to that derived from the conventional maximum likelihood method.

Yoshida et al., (1994) proposed a pattern classification method for remote sensing data using neural network. In order to get the stable and precise classification results, they selected the training data set based on geographical information and Kohonen's self-organizing feature map. After training the neural network, some pixels were deleted from the original training data set if the pixels are incorrectly classified and a new training set is built up. The classification results of LANDSAT TM data show that this approach produces
excellent results, which are more realistic, and noiseless compared with a conventional Bayesian method.

Fitzgerald et al., (1992) applied a BPN network to the task of floristic land cover classification. The input data consists of the three LANDSAT TM bands 2, 4 and 7 and the GIS based environmental variables Aspect, Elevation, Catchment, Geology and slope. The resulting classified image provides a realistic estimate of the distribution of floristic classes in the Kioloa study area. The classifier developed in this study compares favorably with other technique.

Tzeng et al., (1998) applied fuzzy neural network to process the SAR data. The conventional neural network classifier performs learning from representative information within problem domain on a one –pixel-one-class basis: therefore, class mixture and the degree of membership of a pixel are generally not taken account, often resulting in a poor classification accuracy. The fuzzy dynamic learning neural network method has fast convergence rate than those of regular neural network. In addition, the separability between similar classes is improved. Carpenter et al., (1997) developed a method for automatic mapping from Land sat thematic mapper and terrain data based on ARTMAP neural network. They compared the results with the maximum likelihood, Back propagation neural network and K-nearest neighbor algorithms. ARTMAP dynamics are fast, stable, and scalable, overcoming common limitations of back propagation. They obtained best results making the hybrid of convex combination of fuzzy ARTMAP and maximum likelihood predictions. Senthilkumar et al., (1997) used robust classification of multispectral data using multiple neural networks and fuzzy techniques. The fuzzy integral approach found to be superior to that of their individual classification performance. Parviz et al., (1998) also used fuzzy techniques for delineate the mangrove area using IRS satellite image.
Benediktsson et al., (1997) proposed the hybrid of statistical and neural network classifiers. In this method, they considered hybrid classification methods based on consensus from several data sources. Both linear and non-linear optimization methods are considered and used in classification of two multisource remote sensing and geographic data sets. A non-linear method, which utilizes a neural network, gives excellent experimental results. The hybrid statistical/neural network method outperforms all other methods in terms of test accuracies.

Lee et al., (1990) demonstrated that, with high spatial resolution data, very high cloud classification accuracies could be obtained, especially in conjunction with a nonparametric neural network classifier. They used texture based neural network classifier using only single channel visible LANDSAT MSS imagery achieves an overall identification accuracy of 93%. Xiao et al., (1997) developed a neural network based algorithm for rainfall estimation from Radar Observations. The rainfall estimates obtained from neural network are shown better than those obtained from several existing techniques. Hosomura et al., (1993) used neural network to make a relatively cloud free mosaic. They suggested neural network can be meaningfully used as classifiers in situations where the data to be classified is of non-parametric nature. They considered cloud as one class and all the clear sky areas as another class and they used MOS-I data for this study. Xiao et al., (1997) developed ANN based algorithm for Radar snow fall estimation.

Ediriwickrema et al., (1997) used hierarchical maximum-likelihood classification for improving accuracies. It is common practice to perform the maximum likelihood classification with equal prior probabilities. When equal prior probabilities are used, the advantages in MLC classification may not be attained. Their study explored a Hierarchical Pixel Classification (HPC) method to estimate prior probabilities for the spectral classes from Thematic Mapper.
data and spectral signatures. The classified image resulting from the HPC showed increased accuracy.

Alhumaidi et al., (1997) used a neural network algorithm for sea ice edge classification of radar backscatter from sea ice. To prevent contamination of the wind measurements, by the presence of sea ice, algorithm based on neural network technology have been developed to classify ice-free ocean surface. Bischof et al., (1998) used optimal neural networks for land classification, which is fully automatic and computationally efficient algorithm, based on the Minimum Description Length (MDL) principle for optimizing perceptron (MLP) classifiers.

Settle et al., (1997) have devised, written and tested an implementation of the Gaussian maximum likelihood classification method for a commercial image processor. This has resulted in significant savings in execution time for the classification of multispectral remotely sensed imagery, at very little cost to the accuracy, when compared to software version of the same algorithm. Groom et al., (1996) used contextual correction techniques in order to improve the land cover mapping from remotely sensed images. They used the Landsat Thematic Mapper data. The work has involved development of a range of post classification procedures to correct contextual errors associated with the use of spectral classification algorithms. Sudha et al., (1995) used automatic classification of targets using artificial neural networks and Patra et al., (1995) used neural network for invariant image classification. Eckes et al., (2001) used neural network for the classification of sea-ice. Chen et al., (1995) developed dynamic learning neural network and applied to perform the inversion of rough surface parameters. They used Kalman filter technique for training the network.

Shao et al., (2001) related the image classification accuracy with the variation of landscape statistics. They used multiple classification of a Landsat
Thematic Mapper image resulted in 23 thematic maps for an area of 31,660 ha in central Indiana in the United States. They used four land use and land cover types: Urban, agricultural land, forest and water. A common set of reference data was randomly sampled from the image and was used to evaluate the classification accuracy. The classification accuracy of the maps was between 77.6 to 89.2%. The results suggested that the variation of landscape index values is inversely proportional to classification accuracy. Therefore, when classification accuracy is lower, the uncertainties of landscape characterization become higher.

Hung et al., (1994) compared a piecewise linear classifier (PLC) with gaussian maximum-likelihood and parallelepiped classifiers in terms of accuracy and speed. The PLC was developed based on the concepts of the single-sided decision surface, optimal weight vector and seniority decision logic. The PLC was much faster than the GMLC and yet provided similar classification accuracy. Although the PLC was somewhat slower than the PPC, it provided much higher classification accuracy than did the PPC.

1.6 PREVIEW OF ALL THE CHAPTERS

The thesis is organized into six chapters. Chapter-1 gives the introduction, list of objectives, review of literatures with respect to Satellite Remote Sensing, Artificial Neural Networks, Expert Systems and Conventional classifiers, and preview of all the chapters.

Chapter-2 describes the three study areas selected for the research and the satellite image data products used for the research. Chapter-3 describes the methodology adopted for the non parametric classifier and classification different study areas.
Chapter-4 describes how the classification of the different study areas such as Urban, Non Urban and Urban and non Urban areas on different sensors is carried out using parametric classifiers.

Chapter-5 gives the detailed discussion of the study areas classified using the above four classifiers. Chapter-6 summarizes the conclusion of the research obtained from this study.

1.7 SUMMARY

The review of works carried out by the number of researchers enriched the analyst the factors that are to be considered in classifying the satellite image using parametric (MLC, Minimum distance and Contextual) and non-parametric (Artificial Neural Networks) classifiers. The present research is the classification of three study areas such as Urban area (Chennai), Non-Urban area (Pichavaram) and combination of Urban and Non-Urban area (Erode and its Environs) of different sensors using above classifiers. The following chapter describes the three study areas used for the research.