CHAPTER ONE

1.0 INTRODUCTION

1.1 BACKGROUND OF STUDY

Artificial intelligence may be defined as the branch of computer science that is concerned with the automation of intelligent behaviour (Vandal, 2010). However, this definition suffers from the fact that intelligence itself is not very well defined or understood. Although, most of us are certain that we know intelligent behaviour when we see it, it is doubtful that anyone could come close to defining intelligence in a way that will be specific enough to help in the evaluation of a supposedly intelligent computer program, while still capturing the validity of the human mind.

Thus, the problem of defining artificial intelligence became one of defining intelligence itself. What is intelligence?

Intelligence is a capacity of a system to achieve a goal or sustain desired behaviour under conditions of uncertainty. Intelligent systems have to cope with sources of uncertainty like the occurrence of unexpected events such as unpredictable changes in the world in which the system operates and incomplete, inconsistent and unreliable information available to the system for the purpose of deciding what to do next.

Intelligent system exhibits intelligent behaviour. Intelligent behaviour if exhibited is capable of achieving specified goals or sustaining desired behavior under conditions of uncertainty even in a poorly structured environment. Such environment includes an environment where various characteristics are not measurable or where several characteristics change simultaneously and in an unexpected way and where it is not possible to decide in advance how the system should respond to every combination of events.

According to Nikola (2007), an intelligent system exhibits the following behaviour

(i) They should from time to time accommodate new problem solving rules.

(ii) They should be able to analyze themselves in terms of behaviour error and success.

(iii) Once they are to interact, they should learn and improve through interaction with the environment.

(iv) They should learn quickly from large amount of data.

(v) They should have many base exemplar storage and retrieval capability.

(vi) They should have a parameter to present.

Agris (2006) also summarized basic features of intelligent systems as follows:

(i) They have the ability to generate a new knowledge from already existing one.

(ii) They have ability to learn.

(iii) They have ability to sense environment.

(iv) They should have ability to act.

Many research work have been carried out in the area of intelligent system. For instance, Paul (2009) has developed an intelligent system to determine the best soil for different types of crops using artificial neural network. Also, there is an intelligent system to predict weather condition in South Korea using neuro-fuzzy method (Mesia, 2006).

Despite series of research in the area of intelligent based system, enough has not been done in terms of developing an intelligent system in geoinformatics most especially in mineral location and exploration.

Geoinformatics is a field of science that combines geodetic and spatial information processing method with computing hardware and software technology. Therefore, mineral location is one of the major areas of geoinformatics and it is the process of finding ore (commercially viable concentration of mineral) to mine. It is much more intensive and involved. The researchers have carried out different research works in the area of geoinformatics with specific regard to mineral location and explorations.

Different methods were used in such research work. Some used database/ data mining techniques or approach to determine the mineral spread in a specific location.

Some used Bayesian network classifiers (Porwal et al, 2006). Some used Logistic method (Knox-Robinson, 2000), (Luo and Dimitrakopoulas, 2003), (De Quadros et al, 2006), (Carranza et al, 2008). Artificial Neural Network was also used by Singer and Kouda (1996), Brown et al (2000, 2003), Behnia (2007), Skabar (2007), Oh and Lee (2008).

Evidence theory model and Geographical Information System (GIS) were also used. GIS which works on the principle of database has also been used for processing and combining data for mineral allocation (Partington, 2010). Apart from GIS approach, some other approaches have also been used to solve this problem: Weight of evidence model (Agterberg and Bonham, 2005), (Jianping et al, 2005), (Nykanen and Raines, 2006), (Porwal et al, 2006), (Roy et al, 2006) (Nykanen and Ojala, 2007), (Raines et al, 2007), (Oh and Lee, 2008), (Harris et al, 2008), (Benomar et al, 2010).

Apart from the different types of methods used, mineral exploration is a multidisciplinary task requiring the simultaneous consideration of numerous geophysical, geological and geochemical dataset (Knox et al, 2003). The size and complexity of regional exploration data available to geologist are increasing rapidly from a variety of sources such as remote sensing, airborne geophysics, large commercially available geological and geochemical data (Brown et al, 2010). This demands for more effective integration and analysis of regional and geospatial data with different formats and attributes. This needs spatial modelling techniques regarding the association of mineral occurrence with various geological features in qualitative manner. Moreover, reliable geoinformation in form of geological and mineral potential map is very important for exploration and the development of mineral resources.

In a country like Nigeria, mineral resources development has played an important role for sustainable economic development. For the past years, petroleum has been the only mineral which the country relies upon economically. There is high tendency for this mineral resource to be exhausted or for the world market price for this product to fall. If it happens, the economy of the country will be grounded. Therefore ,there is a need for Nigeria to continue searching for more minerals.

Several geological, geochemical and geophysical data have been collected to carry out further research on how to locate and explore other minerals apart from petroleum. Today, several of such data are acquired from various conventional exploration and mining companies. Most of the information is dispersed and kept in analog format. The truth of the matter is that there is no serious effort to convert these data and integrate information for the purpose of locating other minerals, determining the volume or quantity of such mineral, generating a mineral map to aid mining and exploration process. Again, the generated or existing geological information including geological maps do not contain enough relevant and sufficient information to aid location and exploration.

Recently, the National Space and Research Centre was established in Abuja in the Northern part of Nigeria. This centre covers most part of the country with microwave remote sensing data set. But these data sets are neither being processed nor integrated with the available geological data to produce sufficient information for mineral location and exploration.

In this research work, an intelligent geoinformatics system is developed to train hyperspectral remote sensing data set using; Halving algorithm, modified Fuzzy-C means algorithm, Kohonen Self Organizing Map and Adapted Neuro-Fuzzy Inference System (ANFIS). The hyperspectral remote sensing data set will be collected from Nevada, USA satellite. The data is to be collected from Nevada because hyperspectral data is not yet available in Nigeria and since this type of research is not expected to be a local research, data from any part of the world can be used.

With series of research to develop intelligent system, there has not been an attempt to develop such a system in the area of mineral prospecting using the type of automated method we have used. This research work is to develop an intelligent system which combines different algorithms to solve the complex problem of geoinformatics with specific regard to mineral prospecting. The use of the stated methods will go a long way to generate a better result or output.

Unlike previous works that mostly generate numerical solutions, this research work will generate better solutions and comprehensive mineral prediction or location map. This will be so since the intelligent system does not depend on statistical distribution and analyses of data like the previous ones. The system will not depend on the statistical distribution of data neither will it make use of database approach but rather it will be made to be intelligent. The intelligence system developed can be a useful tool in solving series of geoinformatics problems that have to do with mineral prospecting in Nigeria and beyond.

1.2 STATEMENT OF THE PROBLEM

Hyperspectral data are characterized by large size and complexity. This poses a serious problem since data of very large size and complexity will be very difficult to process to obtain relevant information. Despite the fact that the available data are of high dimension and of great complexity, they still contain relevant information in term of mineral prospecting. How do we reduce the size of such data without losing some of the vital information contained? Even after dimensional reduction, how do we process such data to obtain the classes, types and volume of mineral in each of the classes that are present in such data?

Unfortunately, various methods used by different researchers are not sophisticated enough to handle this important task. The major challenge with this research is how to use AI principles to develop an intelligent software that can be used to process hyperspectral data to obtain relevant and vital information that can be used in the area of geoinformatics especially in the area of mineral prospecting.

1.3 AIM AND OBJECTIVES OF THE STUDY

The aim of this research work is to develop intelligent geoinformatics system that can be used for solid mineral prospecting

The objectives of this research work are to develop a system that can:

i. Offer an intelligent based geoinformatics data/information.
ii. Generate from hyperspectral data, numerical solutions that determine the location of existing minerals and the quantity of minerals that are present in a particular location.
iii. Generate mineral location map.
iv. Detect unknown or noble minerals as a group of minerals that is detected for the first time and therefore the name could not be found among the existing minerals used to train the network of the developed system.

1.4 SIGNIFICANCE OF THE STUDY

Data Reduction: The choice of data in terms of its representation and selection is one of the important issues to be considered during hyperspectral data processing. This can actually determine whether the problem is solvable or not. Performing such data reduction in term of its dimensionality by the developed system can be of numerous advantages during the computational process. Hence, the research provided a new direction on how to reduce hyperspectral data for further research work.

Reduction in computational process time: Hyperspectral data by virtue of their nature are extremely very large. Large data can take a longer time for processing. This leads to a drastic reduction in the efficiency of the system. Therefore, it is always better to reduce the dimension of the data during preprocessing stage so as to reduce the processing time. The developed system is able to carry out data reduction to a reasonable size thereby reducing the computational processing time.

Improved result/output: The developed system produced an hybridized algorithm which is an improvement on the existing ones. It is an hybridization of different Artificial Intelligence algorithm. By using appropriate data, the algorithm will be able to learn faster and better. The developed system because of the way it was designed and implemented is able to bring an improved result or output compared to the existing system.

Simplified model: It is always better to construct a simple model. The simpler the model, the better the output or result generated. The developed system made use of highly simple model. This assists the system in generating a good result.

The developed system is able to use both supervised and unsupervised leaning algorithm to train hyperspectral data in other to classify and recognize different types of mineral that are present. The developed system is made to be efficient enough to detect strange data set i.e. data set that do not belong to a particular class in a classified hyperspectral data set.

Though, the intelligent system we have developed is applied in the area of mineral prospecting yet, with some modifications, it can be applied in some other areas of geoinformatics and mining.

To ensure a continued supply of mining products, it is necessary to discover new mineral deposit in addition to those currently being mined. Successful exploration therefore ensures the future of the individual and the world economic well being.

Considering the application domain, the new system has other numerous advantages. For instance, mining industry is very important in the development of any nation. The industry obviously employs reasonable number of the nation workforce. It is perhaps not surprising that its importance to everyday life is still poorly understood and appreciated by people.

Mining is not confined to large scale ore operations, nickel and gold production from goldfields, or bauxite mining to produce alumina. It also includes the mining of silica for the glass industry to produce drinking glasses, car windscreens and window panes. Also, the aggregate used to build roads, clay for house bricks, roof tiles and crockery, copper for electrical wire, and the exotic element like tantalum and yttrium necessary for production of capacitors and other products essential for modern semiconductor technology are products of solid minerals. It also includes coal, petroleum and natural gas that provide power and warmth for the community and a host of associated by-product such as plastics and synthetic fibres.

In order to maintain our living standard, we must continue mining and this requires continued exploration for new deposits of all types. Mineral location or exploration is like looking for a needle in a haystack. So, it is important to keep searching. Moreover, everyone in the modern world, depends heavily on the product of mining. The development of commercially viable mineral deposit is also a key factor in achieving a sound economy. To ensure a continued supply of mining products, it is necessary to discover new mineral deposit to replace those currently being mined. Successful exploration therefore ensures the future of the individual and the world economic well being.

Mineral location or exploration is a scientific investigation of the earth crust to determine if there are mineral deposits present that may be commercially developed. To be able to find new deposit, explorers must have access to the land. This will only be permitted if exploration can be carried out with negligible impact on the natural environment. Modern location methods like the one used in this work is capable of discovering deeply concealed deposits which have eluded earlier explorers.

Almost everything that we eat, drink, live in, fly in depends on the products of the mineral industry for either its components, its production or its source of energy. The exploration, mining and mineral processing industry exist because the consumers demand these product. Mineral occur in earth crust in rare concentration known as mineral deposits. Mining is the process of removing these deposits from the ground. Every deposit, no matter how large, has a finite life and will one day be exhausted. It will not be wise to fold our arms until the minerals are exhausted. There is a need to ensure a continued supply of mineral to meet the need of a growing population. Different types of methods have previously been applied to solve the problem of mineral location/ exploration. For instance, previous authors have used. e.g. Evidence Weight Method, Bayesian Theory, Tree diagrams, Neural Network, GIS e.t.c. Obviously, most of these methods are statistically based method which may bring a lot of inaccuracies and bias in the result obtained. The GIS method also depends purely on database. In other words, the results generated are not producing enough information for the mining industry to locate minerals. This calls for further research work.

Therefore, an attempt is being made to use Artificial intelligent method to solve the problem of mineral location. The system is expected to produce a better result and therefore better information for mineral industry. If the mining industries are boosted, it provides the basic needs for the people; there will be good source of income for the government, individuals, parastaters e.t.c. This will also provide better job opportunities for the citizen. In fact, it will go a long run to boost the economy of the country at large.

1.5 SCOPE OF THE WORK

In this research work, an intelligent system that can process hyperspectral data has been developed. The system was applied in the area of mineral prospecting using hyperspectral data for Cuprite from Nevada, USA as the case study. Hyperspectral Data from other countries or locations can still be used. Though we have applied the intelligent system in one area of geoinformatics, with some modifications it can still be applied in some other areas e.g. it could identify different types of soil, vegetation, land topology in a given hyperspectral data.

1.6 DEFINITION OF TERMS

Expert System: This is a computer program designed to simulate the problem solving behaviour of human who is an expert in a narrow domain or discipline.

Artificial Intelligence: This could be defined as the ability of computer software and hardware to do those things that we as human being recognize as intelligent behavior.

Geo-informatics: This is a field of science that combines geodetic and spatial information processing method with computing hardware and software.

Intelligence: This is the capacity of a system to achieve a goal or sustain desired behavior under condition of uncertainty.

Intelligent System: This is the system that exhibits intelligent behavior.

Mineral Location: This is the act of detecting geographical areas where minerals could be sited and explored.

Mineral: This is a naturally occurring inorganic solid, with definite chemical composition and an ordered atomic arrangement e.g. oil, granite, gold, charcoal e.t.c.

Geology: This is the study of earth crust, its rocks and its history.

Geographical Information System: This is the type of system that deals with spatial and semantic data and provide means to analyze them, using computer hardware and software tools.

Geologic modelling or **Geomodelling**: This is the applied science of creating computerized representations of portions of the Earth's crust based on geophysical and geological observations made on and below the Earth surface.

Spectra Signature: They are specific combinations of reflected and absorbed electromagnetic radiation at varying wavelengths which can uniquely identify an object.

Hyperspectral Data: It consists of large numbers of narrow spectra channel from optical wavelength range.

Data Clustering: It is the process of dividing data element into groups or classes such that items in the same class are as similar as possible and items in different classes are as dissimilar as possible.

Unmixing: It is a method used for estimating and measure abundant fraction in a mixed mineral.

Cluster: Clusters can be defined as objects belonging most likely to the same distribution/group.

Clustering: This is otherwise known as Cluster Analysis. It is the task of grouping a set of objects in such a way that objects in the same group (called **cluster**) are more similar (in some sense or another) to each other than to those in other groups (clusters).

Cluster Center: Mean squared distance from each data point to its nearest center.

Mineral: A mineral, or pel, (picture element) is a physical point in a raster image, or the smallest addressable element in a display device. It is the smallest controllable element of a picture represented on the screen.

Spectrum: An array of entities, as light waves or particles, ordered in accordance with the magnitudes of a common physical property, as wavelength or mass.

Mineral Map: Maps describing the location or the conditions of formation of mineral deposits. These maps are prepared on the basis of records of mineral deposits and data obtained from geological surveying, prospecting, and exploration.

Membership Function: The membership function of a fuzzy set is a generalization of the indicator function for a fuzzy set which assigns a truth value (0 or 1) to each element in a classical set.

Rule Surfaces: A ruled surface can always be described (at least locally) as the set of points swept by a moving straight line. For example, a cone is formed by keeping one point of a line fixed whilst moving another point along a circle. In algebraic geometry, ruled surfaces were originally defined as projective surfaces in projective space containing a straight line through any given point.

Inference Engine: An inference engine is a computer program that tries to derive answers from a knowledge base. It is the "brain" that expert systems use to reason about the information in the knowledge base for the ultimate purpose of formulating new conclusions. Inference engines are considered to be a special case of reasoning engines, which can use more general methods of reasoning.

Module: Each of a set of standardized parts or independent units that can be used to construct a more complex structure.

Supervised Learning: Supervised learning is the machine learning task of inferring a function from labeled training data. The training data consist of a set of training examples. In supervised learning, each example is a pair consisting of an input object (typically a vector) and a desired output value (also called the supervisory signal).

Supervised Learning Algorithm: Analyzes the training data and produces an inferred function, which can be used for mapping new examples.

Unsupervised Learning: Unsupervised learning refers to the problem of trying to find hidden structure in unlabeled data. Since the examples given to the learner are unlabeled, there is no error or reward signal to evaluate a potential solution. This distinguishes unsupervised learning from supervised learning and reinforcement learning.

Back Propagation: An abbreviation for "backward propagation of errors", is a common method of training artificial neural networks. From a desired output, the network learns from many inputs, similar to the way a child learns to identify a dog from examples of dogs.

Novel Mineral: This is a new mineral that has not been earlier detected by the network simply because it is not part of the trained data.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 BACKGROUND

2.1.1 Theoretical Background

Artificial intelligence is one of the newest branches of modern science (Ping et al., 1991). During a short period of time (lasting only several decades), there have been series of developments in the field of science and technology to solve different types of problems existing in the field of Artificial Intelligence.

The complexity of those tasks that can be performed by intelligent system to solve different problems is growing from year to year. By definition, Artificial Intelligence can be defined as a science and technology that is concerned with the development of computer system that is capable of acting as a human being (Tung et al., 1999).

Artificial intelligence again is defined as the science and technology which is concerned with the development of computer system that is capable to think, feel, talk, hear, touch, see, perceive e.t.c.

Artificial intelligence is the intelligence of machine (Sugumaran, 2007). Artificial intelligence can also be defined as the branch of computer science that aims to create intelligence of machine (Turban et al., 2004).

Another researchers Russell and Norvig (2003) defined artificial intelligence as the study and design of intelligent agent, where intelligent agent by Luger and Stubblefield (2004), is a system that perceives its environment and takes actions that maximizes its chances of success. John McCarthy, who coined the term in 1956, defined it as the science and engineering of making intelligent machine (John, 2007).

The field was founded on the claim that a central property of human intelligence- the sapiens of Homo sapiens can be so precisely described that it can be simulated by a machine. This raises philosophical issues about the nature of the mind and the ethics of creating artificial beings. Artificial intelligence has been the subject of optimism and today has become an essential part of the technology in industry, providing the heavy lifting for many difficult problems in computer science (Walker, 2007).

Artificial intelligence research is highly technical and specialized and deeply divided into subfields e.g**.** pattern recognition, fuzzy logic, neural network. The subfield have grown up around particular institutions, the work of individual researchers, the solution of specific problems, longstanding differences opinion about how artificial intelligence should be done and application of widely differing tools.

The central problems of artificial intelligence include such trait as reasoning, knowledge, planning, learning, communication, perception and ability to move and manipulate objects (Turban et al, 2004).

2.2 HISTORY OF ARTIFICIAL INTELLIGENCE

John McCarthy of Massassuttes institute of technology in 1956 presented the idea of Artificial Intelligence. Between 1939 and 1950, there was an emergence of modern computer. This leads to the development of modern digital computer which has the following characteristics:

(1) Because of its relatively large storage capacity, it is able to store large amount of data and information.

(2) It maintains a high speed when processing data / information.

This machine therefore gave the researchers the opportunity to build a system which could emulate some human abilities.

Between 1940 and 1950, artificial intelligence emerged as a separate and independent field of study. Though, earlier before this time, there has been different areas of research which studied different concepts that formed the bases of artificial intelligence. Such areas are therefore integrated to shape artificial intelligence as a main and independent area of studies.

For instance, there was the study of “logic” developed by Alonzo Church, Kurt Gödel and Alan Turing. Literature revealed that “logic” as an aspect of Artificial Intelligence was initially developed by Russel, Tarski and Kleen. The concept of logic included proportional and predicate calculus. This concept demonstrated that acts and ideas from a language such as English could be formally described and manipulated mechanically in meaningful ways.

In 1936, father of Artificial Intelligence, Alan Turning, demonstrated that a simple computer processor could be used to manipulate symbols and numbers. This was later named turning machine.

There was also the study of cybernetics which was introduced by Nabert Laleininer. This contributed immensely to the development of Artificial Intelligence. Cybernetics is the study of communication between human and machine. This field succeeded in closing the gap between human and machine communication. In fact, it is able to bring together many idea between human and machine. It was able to bring together many different concepts such as information theory, feedback central system and electronic computers.

Furthermore, in the early part of 1900, there was the development of formal grammar which was an extension of logic. This brought a lot of improvement to the language theories in linguistics.

Again, as part of early development in Artificial Intelligence, there was a development of digital computer called electronic stored program in the early 1950. This was preceded by the different types of prototype systems. Some of these include: The Mark 1 Harvard Veleny computer (1944); the university of Pennsylvania Moore School of Electrical Engineering ENIAC electronic computer (1947) etc.

Again, Claude Shannon introduced the concept of information theories. Similarly, psychologist came up with the idea of neurological theories models of the brain, Boolean Algebra, switching theory and statistical decision theory. Aristotle, Leibnitz, Babbage and Hollerith among others also contributed not in small measure to the emergence and development of Artificial Intelligence.

The 1950s were generally recognized as the official date of birth of Artificial Intelligence. In fact, in 1956, a workshop was held at Dartmouth College which was well attended by pioneers in this field including John McCarthy, Herbert Simon, Claude Shannon, Allen Newell e.t.c.

2.3 INTELLIGENT SYSTEM

An intelligent system is a system that is able to react approximately to the changing situation without a user's input. An intelligent system is a computer system design to perform a dedicated or narrow range of functions with a minimal user interaction (Wilfried, 2002)

John (2002) refers to Intelligence as the overall effectiveness of an individual mental process, especially his or her comprehension, learning/ recall and reasoning capabilities. Intelligence is the ability to reach ones objective. A system is more intelligent if it reaches its objectives faster and easier (Walter, 1997).

Intelligence of a system is a property of its mind and the mind is the functioning of the brain.

An intelligent system is a system that has its own objectives as well as senses and actuators. To reach its objectives, it chooses an action based on experience(s). It can learn by generalizing the experiences it has stored in its memories. Examples of intelligent system are persons, higher animals, robots, extraterrestrials, a nation e.t.c. (Walter, 1997).

This emerging area of research target non stationary process by developing newer on-line learning method and conventionally efficient algorithm for real time application. One of the important challenges today is to develop methodologies, concepts, algorithms and techniques towards the design of intelligent system with higher level of flexibility and autonomy, so the system can evolve their structures and knowledge of environment and ultimately evolve their intelligence. That is, the system must be able to develop, organize and improve itself. It should be able to evaluate the current situation and come up with a better result. Wireless sensors network, Assisted ambient intelligence, embedded soft computing, diagnostics and prognostic algorithm, intelligent agents, smart evolving sensors, autonomous robotics system e.t.c. are some of the implementation areas of Artificial Intelligence.

2.3.1 Related Work

The development of an intelligent system has been one of the areas of focus in the field of research.

Singer and Kouda (1996) compared the probabilistic neural network with weight of evidence method for the prediction of mineral potential and found probabilistic neural network performance to be better.

Hassan and Jean (1999) also developed an intelligent system for weather prediction using fuzzy logic method. The system was able to predict different types of weather conditions for planting and harvesting different crops. He made use of Fuzzy logic for the implementation of the system. the system actually was tested and was found to perform efficiently well in the area of whether forecasting for planting of crops but can not be applied in the area of mineral prospecting.

Wilfried (2002) was able to develop an embedded intelligent system using a soft computing method. The paper discusses auspicious method for the implementation of intelligent solutions for embedded system. The author did not actually implement an intelligent system but rather compared different methods of developing such a system. The Author therefore did not present any other method of developing or implementing an intelligent system.

Kiny et al. (2002) developed an intelligent system filled physiology tutorial using the concept of Mapping. Different functions were defined and the system appears to be highly dynamic and sophisticated.

Jose et al.(2002) developed a hybrid Generic Algorithm for shop scheduling problem. The chromosome representation of the problem is based on random keys. The schedules are constructed using priority rules in which the priorities are defined by the genetic algorithm. A schedule is obtained and a local search heuristic is applied to improve the solution. The result is tested on a set of standard instances taken from literature and compared with other methods. The computation result validates the effectiveness of the developed algorithm.

Kapageridis (2002) also developed an intelligent system which was titled Artificial Neural Network (ANN) Technology in Mining and Environmental Applications in which the author submitted that a number of mining and environmental related problem have been approached using ANN technology. The author brought serious automation in mining industry with ANN which can utilize large amount of data for design implementation of modules. With this, solutions were propounded for different problems in mining industry which the conventional techniques fail in one way or the other to do.

May and Taylor (2003) developed an intelligent system for knowledge management with pattern recognition. With this research, a lot of management problem is solved. The system actually applies the principle of machine learning as a means of recognizing different patterns.

Robert and Henk (2003) worked on Neuro fuzzy method for nonlinear system identification. According to the author, most processes in industry are characterized by non-linear and time-varying behaviour.

So, nonlinear system identification is becoming an important tool which can be used to improve control performance and achieve robust fault tolerant behaviour. In this research work, Neuro-fuzzy system is developed for non linear system identification.

Artificial neural networks (ANN) has been extensively used in other field of research but is still not used extensively in the area of mineral exploration. Brown et al. (2003) published the result of using Back propagation neural network for mineral prospectivity. Probabilistic neural network is used by Singer and Kouda (1997) to classify deposit into deposit type based on presence or absence of ore and alteration of mineral.

Trina (2004) also developed a system to forecast market volatility using Kalman filter method. The purpose of the study is to discover if Kalman filter can be effectively utilized in Computational Market Dynamics (CMD). The author presented an intelligent mathematical model but it was not implemented. No intelligent system was actually developed.

Wendy et al. (2004) developed an intelligent system to achieve space program goals ranging from reducing the cost and complexity of mission operation to sending manned space craft to places. From the earth, it is not possible with human expert. This work developed an intelligent system which reduces dependency on human experts. The system automates early event detection thereby reducing the dependency on human experts.

Yusko and Evens (2004) developed an intelligent system for qualitative reasoning in the knowledge collective (TKC).

Paula (2005) developed a system for polyhedral approach to solve transportation problem. Jeroine and Bryan (2005) used Neural Network and differential evolution for the prediction of stock returns.

Jay and Yusko(2005) developed a Multi-layer, Multi-Agent framework for information Management in an Intelligent Knowledge base in a PhD. thesis at Graduate College of Illinoise Institute of Technology, This intelligent knowledge Based System Support many information structures- Data, Metadata, Autologies, Reasoning Logic. The intelligent system stored information in a better way that enables them to be more easily accessed by applications and users compared to previous methods.

Patrick and Nial (2005) also developed an intelligent system for evaluating the work of an academic. The paper presented different ideas of evaluating academic activities using intelligent system approach but the author did not implement a particular system to be tested or evaluated.

Wolfram et al.(2005) developed a coordinated Multi-Robot Exploration System. The system is able to choose appropriate target point for the individual robots so that they simultaneously explore regions of the environment.

Yoon-Joo, Byung-Chun and Se-Hak-Chun (2005) also developed an intelligent system for medical diagnosis. The system titled: “New Knowledge Extraction Techniques using probability for case-based reasoning. Application of this system in the medical sector has been of good assistance.

Claire (2006) developed an intelligent system called swarm intelligent optimization of time capacitated Arc Routine problem using neural network. The intelligent system was developed using swarm intelligent optimization of time. the system appeared a bit complex. The same system could have been developed using Genetic algorithm to produce better result. Again, the system can not be applied in the area of mineral prospecting.

Mansour et al. (2006) developed neuro-computing based model for anomaly recognition in geochemical exploration. This system was a novel approach for quantitative recognition between blind anomalies and false anomalies pattern using back propagation Artificial Neural Network. In this system, Artificial Neural Network (ANN) model was developed which comprises three steps: Learning, validation and application. During the leaning step, the Neural network were provided with different combination of data for pattern recognition purposes and neural network modified its internal representation by changing the values of its weight to improve the mapping of inputs to output relationship. At the validation stage, the network was fed with set of data as new inputs and the network mapped the input to input relationship based on previously learned pattern. Once the learning and validation steps were completed, the application data which were much larger than the leaning and validation data set were used to generate exploration information. The output is in form of two distinct types of false anomalies (false) and blind mineralization (true). The application of this method does not need any information related to input data.

A Neuro-fuzzy intelligent system for a Bibed Robotic System was developed by Djitt and Hataitep (2006). The article summarizes the basic principles and concepts of intelligent control implemented in a humanoid robotics as well as recent algorithm being devised for advance control humanized robot. The authors presented an Intelligent Neuro-fuzzy for robot with a study of its stability concept during dynamic walking and force measurement system. Some experimental results were presented with remark on future direction.

Pawalai et al. (2006) propose a number of methods for predicting the regional scale prospectivity for gold deposit as well as quantifying the uncertainty in the prediction. The approaches used are based on bagging technique applied to the ensemble of Neural network and interval neurosophic sets. Ensemble of Neural network was found to be better and less erroneos than a single network going by the experiment conducted in this work. The paper applies bagging technique and interval neurosophic sets to essemble of neural network for mineral prospectivity prediction and uncertainty assessment. The research confirmed that the developed system using an equal weight combination produces a better accurate result than those using dynamic weight combinations.

Going by the research work conducted by Gary et al. (2007), the selection of software design pattern is better handled by an expert system. This research work is titled “An Expert System for the Selection of Software Design Pattern.”

Edward (2009) developed an intelligence system to minimize internet fraud. This program provides an overview of the use of current AI technique as a means of combating transaction fraud.

Florian et al. (2009) developed a Neuro-fuzzy system automating parameter optimization of inverse treatment planning. Parameter optimization is the process of inverse treatment planning for Intensity Modulated Radiation Therapy (IMR). It is mainly conducted by human planners in other to locate or to create a plan with desired distribution. To automate this tedious process, an artificial intelligent guided system was developed and examined.

Iyer et al. (2009) developed an intelligent system making use of Polynomial Neural Network (PNN). The system is used in the area of Mineral Prospectivity Analysis in a GIS environment. The system was developed for analysis of mineral prospectivity and it was able to predict deposit and barren cells. PNN is a flexible NN whose topology is not predetermined but developed through learning. The type of method adopted for their design is group method of data handling. Different regression values are computed for the input variable and the best for survival is chosen. More layers are built based on the termination criterion which continues until the network stop getting better. This penalized the model from becoming complex and in turn prevents overtraining.

Iyer et al. (2009) defined a class of neural network architecture called the polynomial network which is used to predict deposit on barren cells. From this research work, one can conclude that the Polynomial Neural Network (PNN) has a good learning capability in determining the number of nodes and hidden layers but Back Propagation Neural Network (BPNN) has to be resolved with trial and error method. In particular, the result from PNN was found to be better than that from BPNN. A lot of research articles have been published in making use of neural network but no emphasis has been placed on mineral prospecting (Pawalai et al, 2006).

Johnny et al. (2009) also worked on General Rate convolutional decoder based on Neural Network with stepping criteria. In this work-a novel algorithm for decoding a general rate K/N convolutional code based on current neural network is described and analyzed. Most importantly, this algorithm allows parallel signal by processing which increases the decoding speed and accommodates higher date transmission.

Timothy et al. (2009), “Symposium on progress in Information and Communication Technology” This research work developed an intelligent Business system which could be applied in various industries such as transportation, banking, health care etc.

Folorunso et al. (2012) developed a system called a rule based expert system for mineral identification. The idea is that human expert is programmed into the machine in form of an artificial intelligence. The physical properties of the minerals were used as the basis for their classification or identification. This serves as the knowledge domain of the system. The type of inference engine developed is a rule based inference engine. The system was implemented using Visual Basic.

Saxena et al.(2010) developed an intelligent system for emerging power system to solve the problem of power design, planning and distribution using computational intelligence technique. This system solves the problem of using conventional method which created a lot of difficulties of derivative existence and provide optimal solutions. The author made series attempts to review and discuss the various tools or techniques used in Computational Intelligent and drew some comparison. But there was no intelligent system developed.

Ruifeng et al. (2010) developed an intelligent system for production scheduling. Production scheduling problem is a typical combinational optimization problem in a manufacturing system. An integrated model (Intelligent System) which can cope with the whole multilevel scheduling information simultaneously, using metaheuristic algorithm, a generic algorithm (GA) and simulated annealing was implemented. The result shows that the system out-performed the other ones.

Simonelli (2010) also developed an intelligent system titled “Black Sholes Fuzzy Numbers as indexes of performance”. The system was tested with data of Italian Stock Exchange to forecast the nature of the future market. In 2004 and 2006, the index obtained from the intelligent system is negative which indicates refusal for investment. November 11, 2006, the system could forecast that the market will become more risky. Obviously, with respect to the probabilistic tree, the intelligent system is more simple and immediate to have a forecast on the financial market.

Daoxing et al. (2010), in their research work; A review of Gait Optimization Based on Evolution Computation using computational methods. This paper reviews the techniques used in evolution based Gait optimization. The paper also addresses further possible improvement in efficiency and quality of the intelligent system. The conclusions is that Evolutionary Computation (EC), including Generic Algorithm (GA) and Generic Programming e.t.c. will be good choice for the Gait optimization of legged Robot.

Hojjat and Siamak (2010) developed an intelligent system which introduces route selection system using fuzzy logic for local pheromone updating of an ant colony system in detection of optimum multi parameter directions between two desired points, origin and destination (O/D). In this system, online traffic data are supplied directly by a Traffic Control Center (TCC) and further minute traffic data are predicted by applying Artificial Neural Network. The developed system was simulated on region of London, United Kingdom and the results are evaluated.

Jiancheng (2010) developed an intelligent propositional logic system titled Consistency Degree of Theories in Łukasiewicz fuzzy and n-valued propositional logic system. The system is able to produce necessary and sufficient conditions for theory to be consistent and fully divergent.

Tohru (2010) developed a new robust Receding Horizon Control (RHC) design approach for the sample data system. The approach is based on a dividing generic computation of minimax optimization for a robust finite recording horizon control problem. Numerical example is given to show the effectiveness of the developed method.

De falco et al. (2010) developed an intelligent system called Distributed-Bio-Inspired Method for Multisite Grid Mapping. The intelligent system developed made use of computational techniques to assemble multisite and multiowner resources and presented the most promising solution for processing distributed computationally intensive applications, each composed by a collection of communicating task. The aim is to minimize the time required to complete execution of the application. The system was able to reduce the use of Grid resources.

Nurdan and Nihat (2011) developed an intelligent system that made use of Multiple Layer Artificial Neural Network K-fold cross validation. The system used AI for the classification of minerals based on colour values of mineral. A feed forward Multiple Layer Perception Neural Network (MLPNN) is one of the popular models. A feed forward MLPNN trained with back propagation algorithm is quite good for classification and therefore was adopted in the development of this system. The accuracy of the system using ANN was between 90.67 and 97.62%.

Saro Lee Hyun-Joo (2011) developed an Artificial Neural Network for Mineral Potential Mapping. This research work developed spatial modeling technique such as weight of evidence model, Bayesian Network classifier, logistic regression model, artificial neutral network and GIS. This artificial neutral network has an advantage compared with statistical methods. The artificial neutral network is independent of statistical distribution of data and there is no need of specific statistical variable. Again, if compared with statistical method, natural network allow the target classes to be defined with much consideration to their distribution in the corresponding domain of each data source. The objective of this study is to set some cases for the selection of training data using quantitative mineral potential index by likelihood ratio, weight of evidence and logistic regression model, generate mineral potential map (gold-silver) in the Taebaeksan mineralized district, Korea.

Biaobiao et al (2011) developed an intelligent Evolutionary system using Neural Network and fuzzy logic. The system is a Neuro-fuzzy system. In this system, there is application of Evolutionary Algorithm which leads to the construction of intelligent system using Neural Network and Fuzzy logic.

Another Artificial Intelligence research was developed by Rasim et al. (2011). The research work has to do with the classification of Textual E-mail using Data Mining Technique. The purpose is not only to filter messages into spam but still to divide spam messages into thematically similar groups and to analyze them in order to design the social network of spammers. Generic Algorithm (GA) was used to solve the clustering problem.

Sakin ah et al. (2011) presented an intelligent system research that is concerned with Data future reduction in fuzzy modeling through particle swarm optimization. In this research work, a fuzzy model meant for data and feature reduction was developed. A series of numeric experiment using several machine learning data set were carried out with the system.

Anand et al. (2011) developed an intelligent system titled a Probability Collective Approach with Feasibility Based Rule for Constrained Optimization. This research attempt to incorporate a simple and generic constraint handling technique to the probability collectives (PC) approach for solving optimization problems. It optimizes any complex system by decomposing it into smaller subsystem and further treats them in a distributed and decentralized way. The system is shown to be sufficiently robust and the strengths and weakness of the methodology are also discussed.

Similarly, Farghaly et al. (2012) developed a system for Optimizing the Egyptian Coal Flotation using an Artificial Neural Network (ANN). In this system, back propagation Neural Network (NN) is used for optimizing a coal flotation process. The optimum value of flotation time, collector dosage, frother dosage and flotation cell impeller speed are determined by ANN. The training of the NN is based on back propagation algorithm

Maurice and Hordur (2012) developed a robot that could constantly navigate through changing surrounding with virtually no input from human. This system builds and conclusively updates a 3 – dimensional map of their environment using a low cost camera. In other to enable an environment and to detect minerals, a root Robot needs to be able to map them as they move around estimating the distance between themselves and nearby walls and to plan route around any obstacle. But while a large amount of research has been devoted to developing maps that a robot can use to navigate around an area; this system cannot adjust to changes in the surrounding over time but with new approach based on technique called simultaneous localization and mapping, it will allow a robot to constantly update a map as they learn new information within the environment. As the robot travels through an unexpected area, the kinetic sensor's visible light video camera and infra-red depth sensor scan the surrounding, building up a 3 – D model of the environment and the various objects within it. When the robot passes through the same area again, the system can recognize features of the new images hence, detecting rock and mineral deposit. At the same time, the system constantly estimates robots' motion using on-board sensors that measure the distance the wheels have rotated. By combing the visual information with the motion data, it can determine where within the environment mineral rocks are located. Combining the two sources allows the system to eliminate errors that might creep in if it relies on robot and board sensor alone. Once the system is certain of its location, any new feature that has appeared after previous picture was taken can be incorporated into the map by combining the old and new images of the scene.

Masafumi and Satoshi (2012) designed and implemented an intelligent mobile phone based on Artificial Neural Network. This intelligent system is able to translate number segments into the intended words because the system becomes aware of correspondence of number segment through learning by Artificial Neural Network. The systems do not need a dictionary. The effectiveness of the system was demonstrated practically using twister data.

Damousis and Argyropulos (2012) developed an intelligent system for Machine Learning Algorithm for Biometric fusion. The system used Gaussian Mixture Model (GMM), Artificial Neural Network (ANNs), Fuzzy Expert System and Support Vector Machine (SVM). The comparison of the algorithms reveals that the biometric fusion system is superior to the original unimodal systems and other fusion schemes found in Literature.

Shipra et al. (2012) use Generic Algorithm (GA), Adaptive Neuro Fuzzy Integrated System (ANFIS) as Soft Computing forecasting models for stock market prediction and financial forecasting. This research Modeling Chaotic Behaviour of Chittagong Stock indices. The use of soft computing models is more successful than time series model

Masao (2012) in a work "Computing in Spatial Language Understanding Guided by Cognitively Inspired Knowledge Representation" a human friendly intelligent system which is necessitated by increase in age, society, floods, development of robot for practical use e.t.c. was developed. This system is able to develop a computable knowledge of representing spatiotemporal event perceived by people in the real world. So, the intelligent system produces a model of human mental image and its description language.

Xiuming et al. (2012) used the concept of pattern recognition to generate algorithm for Discovery Access Pattern recognition from web log data. This research is a typical sequential pattern recognition application and a lot of access pattern mining algorithms were developed.

Kurosh et al.(2012) presented a research work titled Multilevel Cognitive Machine-Learning-Based Concept for Artificial Awareness and its Application to Humanoid Robot Awareness Using Visual Saliency. The research accosts the robots intelligence from a different slant directing the attention to combining both "cognitive" and "perceptual" abilities. Within such a slant, the machine (robot) shrewdness is constructed on the basis of a multilevel cognitive concept attempting to handle complex artificial behaviours. The system was able to proffer the robot autonomy and awareness in and about unknown backdrop.

Geev et al. (2012) developed a fuzzy controller for improving fault Ride-Through (FRT) capability of variable speed Wind Turbine (WTs) equipped with Duly Fed Induction Generator (DFIG). Simulation carried out on real bus Italian weak distribution system confirmed that the controller can enhance the FRT capability in many cases.

Folorunso et al. (2012) developed an expert system titled Rule Based Expert System for Mineral Identification. The idea is that human expert is programmed into the machine in form of AI. The work involves the use of expert system in mineral identification. The design and implementation of expert system is based on mineral characteristics of the 40 minerals involved in the study as knowledge domain. The inference engine is rule based. This system depends totally on the expert knowledge and therefore can only identify limited number of minerals as specified in its database. But, the system will be of great assistance where there are insufficient expert to analyze and interpret solid minerals. Loss of vital knowledge through the death of expert can equally be combated by back up storage.

Abedi et al. (2013) applied fuzzy Analytical Hierarchical Process (AHP) method to integrate geophysical data in prospect scale, a case study of Seridune Copper deposit. The developed system made use of fuzzy knowledge base method to integrate different geophysical dataset in other to prepare mineral prospecting map.

Numan,Elmas and Ugur (2013) developed an intelligent system for Computation of Grade Values of Sediment-highted Barite Deposit in Northeast Isparta (Western Turkey). In this study, the author developed a system that was applied for prediction of grade values. The system made use of adaptive Neuro-Fuzzy (NF) Inference System. The spatial coordinates X, Y and Z of the study area were used as input variable in the system.

In NF modeling, different learning techniques using Neural Network are combined with fuzzy rules to arrive at a better solution. Artificial Neural Network (ANN) are capable of learning from a set of input output data. ANN is able to learn through its learning algorithm and is able to mimic the learning mechanism of biological system. The system is a Multi-Layer Perception (MLP) system. A MLP is a non-parametric technique for performing a wide variety of detection and estimation task.

2.4 MINERAL EXPLORATION / LOCATION

Mining industry is very important to the development of any nation (Behnia, 2005).The industry obviously employs reasonable percentage of the nation work force. It is perhaps not surprising that its importance to everyday life is still poorly understood and appreciated by people.

Moreover, everyone in the modern world depends heavily on the product of mining. The development of commercially viable mineral deposit is also a key factor in achieving a sound economy (Oh & Lee, 2008).

Mineral location/ exploration is a scientific investigation of the earth crust to determine if there are minerals deposit present that may be commercially developed (Carranza et al., 2008).

Mineral occur in earth crust in rare concentration known as mineral deposit. Mineral location is the process of detecting and confirming the presence this mineral deposit in the ground.

The concept of mineral location/ exploration therefore is deeply being studied in geoinformatics. Geoinformatics is the science which develops and uses information science infrastructure to address the problem of geosciences and related branches (Harries et al, 2008). Therefore, the study of Geographical Information System becomes very relevant in the study of Geoinformatics.

2.5 THE CONCEPT OF GEOGRAPHICAL INFORMATION SYSTEM (GIS)

The day to day necessity of dealing with space and spatial relationship represents one of the basic facets of human society. This brought about the concept of GIS.

GIS is defined as having functional capability to bring together spatial data from large variety of sources into a single data base as a series of data layers that overlap capacity at all locations (Bonham, 1994).

GIS evolved as a means of assembling and analyzing diverse spatial data. This system evolved from centuries of map making and the compilation of registers. The earliest maps were drawn on patchment to show the gold mines at coptes during the region (1292-1225 B.C) of Rameses II of Egypt. At a later date, the Greek acquired cartographic skill and compiled the realistic maps.

The Greek mathematician, astronomer, and geographer era (ca 276-194. B.C) laid the foundation for scientific cathography i.e. the science, art and technology of making, using, and studying maps. The Arabs were the leading cathographers of the middle ages.

The Arabian geographer AI-idrisi made a map of the world in 1154. European cathography generated as Roman Empire fell. Until the 19th century, geographical information was used mostly for trade and exploration by land and sea and for tax collection and military operations. New need arose in steps with evolving infrastructures such as roads, railway e.t.c. because planning these facilities required information about the terrain beyond that commonly available. As planning advanced, specialized maps became more common. In 1838, the Irish government compiled a series of maps for the use of railway engineers which may be regarded as the first manual geophysical lifting system.

By the late 1950s and early 1960s, Seland generation computers using transistor became available and the first computerized GIS appeared. The first GIS was Canada GIS (CGIS) designed in the mid 1960s as a computerized map measuring system.

CGIS was developed by Roger Tanlinsan and colleagues for Canadian land inventory. This project pioneer much technology and introduced the term GIS. The rapid development of powerful computer leads to an increasing acceleration in the use of GIS.

In the 1970 and 1980s, various systems evolved to replace manual carthographic computations workable production system became available in the late 1970’s. GIS really began to take off in the early 1980s, when the price of computing hardware had fallen to a level that could sustain a significant software industry and cost effective application.

The market for GIS software continued to grow, computer continues to fall in price, and increase in power, and the software industry has been growing ever since (Clarke, 1999).

The decade 1987-1997 has seen the introduction of GIS to geosciences, and its application to mineral location and exploration. GIS provides a computing environment for handling images, maps and data tables, with tools for data transformation, visualization, analysis, modeling and spatial decision support (Bonham, 1990). Methods integrating exploration data sets for mineral potential mapping are facilitated by GIS and can be either knowledge driven or expert system driven depending on the level of prior exploration.

The experience gained with these methods to date demonstrate that they are invaluable for formalizing exploration models for providing a basis of communication between individuals with different background and perspectives, for quantifying spatial association of mineral occurrences with data layers and for identifying prospective areas for follow-up.

Statistical methods such as multiple linear regressions were one of the earliest methods used in the mineral potential mapping. But, the method is based on the assumption that the relationship between the input and output is linear. Obviously, this is not always true.

Mandy and Gavin (2009) look at the application of fuzzy logic set theory in GIS to identify potential areas for mineral development. Arc-SDM (Spatial Data Modeller) was used to assign fuzzy membership value to the selected criterion and calculate a combine output surface indicating the potential areas for gold mineral development based on fuzzy set membership.

This research work depends on GIS package called Arc-SDM (Spatial Data modeller) which is an extension of Arc Map that provides conditional geoprocessing and modeling functionality. It is not an automated system.

Iyer et al (2009) uses a class of neural network known as the polynomial neural network to construct a model to correctly classify given location into deposit and barren areas. This model uses GIS data of the location. The method is tested on GIS data for kalgoorlie region of Western Australia.

2.6 RESEARCH WORK IN GEOINFORMATICS

Geoinformatics is a science which develops and uses information science infrastructure to address the problems of geosciences and related branches of science and engineering.

The 3- main tasks of geoinformatics are:

(i) Development and management of database of geodata.

(ii) Analysis and modelling of geodata.

(iii) Development and integration of computer tools and software for the first two tasks

Geoinformatics is related to geocomputation and to the development and use of GIS.

Numerous research works have been conducted and published in the field of geoinformatics with specific regards to mineral location and exploration.

Also, GuoCheng and DeVerie (1991) presented a model which is being referred to as geology-exploration and endowment model. This model differed from conventional ones by extracting and utilizing geosciences information from both geological features and exploration factors.

Knox (2000) used vectorial fuzzy logic to display prospectivity of mineral exploration as a continuous surface and allowed measure of confidence to be incorporated into the system. This research though produced a good numerical result, failed to incorporate relevant maps.

Rigol-sanchez et al. (2003) developed a back propagation artificial neural network model to discriminate zone of high mineral potential in a gold field using remote sensing neural network with 3 hidden units were selected by means of k-fold cross validation method.

The trained network was able to estimate a gold potential map efficiently. It indicated that both previously known and unknown potentially mineralized areas can be detected. Though, this research made use of neural network, but it is not a full automated system and only made use of GIS packages.

Andrew (2005) presented a multilayer perception approach to output value that can be interpreted as representing mineral posterior probabilities. The technique is applied to mapping gold mineralization potential. The method is purely a statistical method.

Harriset al,(2006) discussed different methods to create favourability map through georeferenced data integration for mineral location and exploration. He was able to establish spatial correlation between known occurrence and tested variables using Baye’s probability theory. Spatial zone was used around the known deposit to determine the statistical criteria to apply to data layers in other to predict the presence or absence of mineral deposit.

This is of statistical approach and therefore the favourability maps generated are not comprehensive in terms of the information that could be generated from the map.

Many potential assessment studies based on georeferenced data integration were also published for various ore deposit. Orogenic gold deposit (Groves et al., 2000), (Lamothe, 2008), epithermal gold deposit (Boleneus et al., 2001), kimberlite potential (Wilkinson et al., 2000).

It is also possible to combine two types of approach to develop hybrid method for mineral location and deposit. For example, to access the mineral potential for SEDEX-type in India (Porwal et al., 2008), for orogenic gold deposit in the Abitibi region (Lamothe and Haries, 2006); (Lamothe, 2008). These authors used the weight of evidence method to weigh parameters of the new area of interest and Neural Network. These studies concluded that there were precious metals in Laplata Mountain. However, the researchers did not come with spatial analysis of correlate geochemical anomalies, surface geology and structural features in the region.

Though, Suslick et al. (2009) claimed to have improved on this by introducing the decision tree along with other statistical method. But the fact that the research also depended on statistical data, principle and estimation limited the result obtained though better than the previous work.

Daniel et al. (2009) worked on the location of high favourability zone copper deposit. The research work defines high favourability zone based on grouped parameters. The geological relevance of each parameter is weighted using weight of evidence spatial analysis method.

Laercio, et al. (2009) presented a research work in macroscopic rock texture image classification using fuzzy class method. This work is to help in diagnosis and planning of oil reserviour exploration. This method was capable of generating its own decision structure.

Irmiya and Shadrach (2010) applied Geographic information system software for mineral exploration in Nigeria. They were able to identify major areas of GIS application in Nigeria mineral industry.

Resistivity profiles from North Central part of Nigeria were digitalized into GIS to delineate fourmaline and Chalcopyrite resources. The result demonstrated the potential of GIS in speedy and reliable execution of mineral exploration project as demonstrated in this work, GIS can provide a very speedy and reliable tool for geological mapping, geophysical survey and interpretation as well as mineral reserve estimation of different mineralization in Nigeria. There is a need to support this work with an intelligent system which will particularly stimulate the application for mineral exploration in Nigeria.

Greg (2010) developed wind and mineral exploration models using GIS for project development in Agentina. The techniques have been successfully used to map wind farms location in New Zealand and rank each site according to its economic potential. Spatial modeling techniques were used to map potential mineral exploration opportunities for gold, copper, base metals, tin e.t.c. at a regional scale in Argentina and Chile. Regional scale prospectivity models were developed for Argentina and Chile to identify prospective areas for variety of metals and mineralization styles, fuzzy logic technique were used to develop mineral potential map in Argentina and Chile. The model has successfully identified areas that are prospective for wind energy and gold, copper and silver and has also identified areas where new mineralized system could be discovered with further exploration and development. It is useful to identify variety of minerals, but it is not an automated system. This calls for an Intelligent System to be developed.

Going through the literature, one can conclude that though series of research have been carried out in geoinformatics using different types of method for instance some used weight of evidence, Bayesian Network Classifier, Artificial neural network, evidence theory model, GIS, Bayesian theory, Decision trees, etc. It is glaring that none of the authors has developed an intelligent system to solve the problem of mineral location. This research work is not just concerned with the development of intelligent system but implementing such system with hybridization of different algorithms.

The research will therefore produce a better result for mineral location and serve as a very useful "tool" in the mining and other related industries.

2.7 ARTIFICIAL INTELLIGENCE TOOLS

2.7.1 Adaptive Neuro-fuzzy inference system

Neuro-fuzzy system represents connection of numerical data and linguistic representation of knowledge. The structure of a neuro-fuzzy system is similar to a multi-layer neural network. In general, neuro-fuzzy system has input and output layers, and three hidden layers that represent membership functions and fuzzy rules. Encoded fuzzy system in several layers of neural network can be in form Mamdani or Sugeno fuzzy interface model. Using network learning ability, the parameters can be adapted, hence the system is called adaptive Neuro fuzzy inference system (ANFIS) Negnevitsky (2005).

2.7.1.1 Adaptive Neuro Fuzzy Inference Method

The fuzzy logic and fuzzy inference system (FIS) is an effective technique for the identification and control of complex non-linear systems. Fuzzy logic is particularly attractive due to its ability to solve problems in the absence of accurate mathematical models (Sugeno, M. and Yasukawa, T, 1993). Surface roughness modeling in turning is considered complex process, so using the conventional techniques to model the surface roughness in turning results in significant discrepancies between simulation results and experimental data. Thus, this complex and highly time-variable process fits within the realm of Neuro-fuzzy techniques. The application of a Neuro-fuzzy inference system is used for prediction and overcomes the limitations of a fuzzy inference system such as the dependency on the expert for fuzzy rule generation and design of the non- adaptive fuzzy set.

2.7.1.2 Structure of Adaptive Neuro-Fuzzy Inference System

Adaptive Neuro-fuzzy inference system is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and approximate membership functions from the stipulated input-output data pairs for neural network training. This procedure of developing the framework of adaptive neural networks is called an adaptive Neuro fuzzy inference system (ANFIS). There are two methods that ANFIS learning employs for updating membership function parameters:

1) Back propagation for all parameters (a steepest descent method), and

2) A hybrid method consisting of back propagation for the parameters associated with the input membership and least squares estimation for the parameters associated with the output membership functions.

As a result, the training error decreases, at least locally, throughout the learning process. Therefore, the more the initial membership functions resemble the optimal ones, the easier it will be for the model parameter training to converge. Human expertise about the target system to be modeled may aid in setting up these initial membership function parameters in the FIS structure, Jang (1993), Jang, J.S.R., Sun, C.T., and Mizutani, E., (1997). The general ANFIS architecture is shown in figure 2.1 below

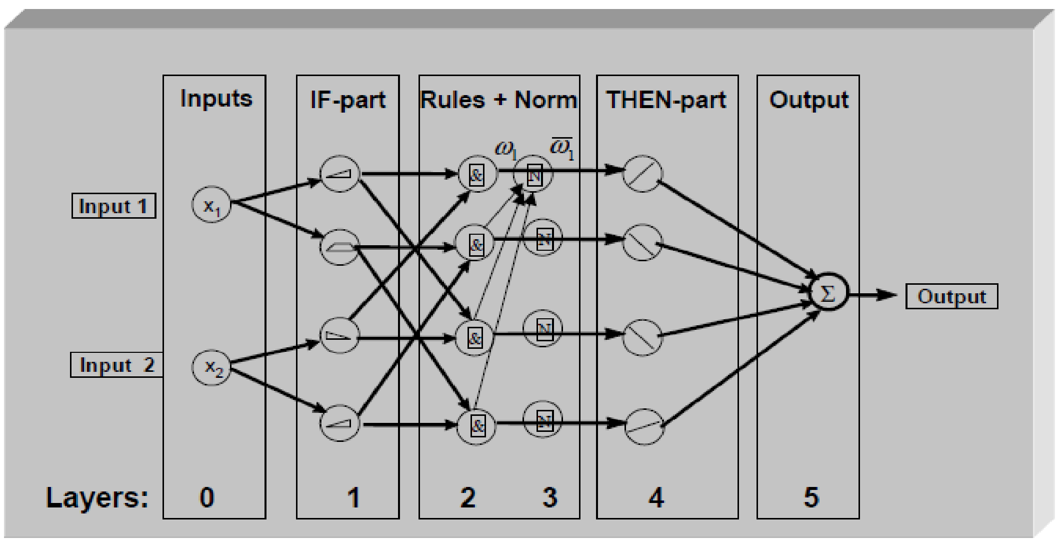


Figure ***2.1: The General ANFIS Architecture***

Five network layers are used by ANFIS to perform the following fuzzy inference steps. (i) Input Fuzzification, (ii) Fuzzy Set Database Construction, (iii) Fuzzy Rule Base Construction, (iv) Decision Making, and (v) Output Defuzzification.

For instance assume that the FIS has two inputs x_1 and x_2 and one output y. For the first order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as:

$$Rule\ 1: IF (x_1\ is\ A_1)\ AND\ (x_2\ is\ B_1)\ THEN\ f_1 = p_1x_1 + q_1x_2 + r_1 \quad \ldots..(2.1)$$

$$Rule\ 2: IF\ (x_1\ is\ A_2)\ AND\ (x_2\ is\ B_2)\ THEN\ f_2 = p_2x_1 + q_2x_2 + r_2 \quad \ldots.(2.2)$$

Where A_1, A_2 and B_1, B_2 are the membership functions for the input x_1 and x_2, respectively, p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output function. The functioning of the ANFIS

Layer 1: Calculate Membership Value for Premise Parameter

Every node in this layer produces membership grades of an input parameter. The node output

$$o_{l,i} = \mu_{Ai}(x_1) \; for \; i = 1,2, or \qquad \dots.(2.3)$$

$$o_{l,i} = \mu_{Bi-2}(x_2) \; for \; i = 3,4 \qquad \dots.(2.4)$$

Where x_1 (or x_2) is the input to the node i; A_i (or B_{i-2}) is a linguistic fuzzy set associated with this node. $O_{1,I}$ is the membership functions (MFs) grade of a fuzzy set and it specifies the degree to which the given input x_1 (or x_2) satisfies the quantifier. MFs can be any functions that are Gaussian, generalized bell shaped, triangular and trapezoidal shaped functions. A generalized bell shaped function can be selected within this MFs and it is described as:

$$\mu_{Ai}(X_1) = \frac{1}{1 + \left|\frac{X_1 - c_i}{a_i}\right|^{2b_i}} \qquad \dots..(2.5)$$

Where a_i, b_i, c_i is the parameter set which changes the shapes of the membership function degree with maximum value equal to 1 and minimum value equal to 0.

Layer 2: Firing Strength of Rule

Every node in this layer, labeled Π, whose output is the product of all incoming signals:

$$o_{2,i} = w_i = \mu_{Ai}(x_1)\mu_{Bi}(x_2) \; for \; i = 1,2 \qquad \dots..(2.6)$$

Layer 3: Normalize Firing Strength

The i^{th} node of this layer, labeled N, calculates the normalized firing strength as,

$$o_{2,i} = \overline{W}_i = \frac{W_i}{w_1 + w_2} \quad i = 1,2 \qquad \dots.(2.7)$$

Layer 4: Consequent Parameters

Every node i in this layer is an adaptive node with a node function,

$$o_{4,1} = \overline{W}_i f_i = \overline{W}_i(p_i x_1 + q_i x_2 + r_i) \qquad \dots..(2.8)$$

Where i is the normalized weighting factor of the iwth rule, f_i is the output of the ith rule and p_i, q_i r_i is consequent parameter set.

Layer 5: Overall Output

The single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals:

$$Overall\ output\ =\ 0_{5,i} = \sum_i \bar{W}_i f_i = \frac{\sum_i W_i f_i}{\sum_i W_i} \qquad \ldots..(2.9)$$

ANFIS requires a training data set of desired input/output pair (x_1, x_2…x_m, y) depicting the target system to be modeled. ANFIS adaptively maps the inputs (x_1, x_2…x_m) to the outputs (y) through MFs, the rule base and the related parameters emulating the given training data set. It starts with initial MFs, in terms of type and number, and the rule base that can be designed intuitively. ANFIS applies a hybrid learning method for updating the FIS parameters. It utilizes the gradient descent approach to fine-tune the premise parameters that define MFs. It applies the least-squares method to identify the consequent parameters that define the coefficients of each output equation in the Sugeno-type fuzzy rule base. The training process continues till the desired number of training steps (epochs) or the desired root mean square error (RMSE) between the desired and the generated output is achieved. In addition to the training data, the validation data are also optionally used for checking the generalization capability of ANFIS.

2.7.2. Expert System

Expert system is one of the major areas of AI that has to do with scientific method of making machines to acquire human expert knowledge to solve a particular problem in a given domain. Expert system can explain why data is needed and how conclusions were reached.

ES can be defined as computer program that combine expert knowledge in a particular domain and disseminate to others. An expert system is a program that emulates the interaction a user might have with a human expert to solve problem in a particular domain. (Samy et al, 2008)

The system continues to ask questions from the end user and expect the end user to supply answers as input by selecting one or more from options provided by the system or by entering another set of data as input. Such interaction will continue until the system reaches the conclusion. The solution arrived at may be an exact solution i.e. single solution or multiple solutions arranged in logical order. The system will equally explain the reason why it arrives at such conclusion.

ES has ability to utilize incomplete or incorrect data. In fact, giving only a partial data set, an expert is likely to produce accurate result with high degree of certainty in its conclusion. The degree of certainty can be qualified in relative terms and concluded in knowledge base. The certainty values are assigned by the expert during the knowledge acquisition place of developing a system.

2.7.2.1 Advantage of Expert System

(i) With expert system in place, the probability and the frequency of making good decision is high. This facilitates a sort of consistency in decision making. The development of expert system to solve different real life problem has made it possible to distribute human expert.

(ii) In most cases, the development of expert system will reduce the cost of decision making i.e. the availability of ES make proper and effective use of available data.

(iii) It permits objectivity by weighing evidence without bias and without regards to the user's personal and emotional reactions.

(iv) It made it possible for human experts to have free time and mind to concentrate on some other meaningful activities.

(v) ES support modular structure. This thereafter paves way for high degree of dynalism in solving real life problems.

2.7.2.2 Expert System Methods

ES adopts different types of methods. Some of these methods include:

Heuristic Reasoning: This is the type of method the human expert will adopt in solving problems. It could be referred to as rules thumb or expert heuristics. This method allows the expert to arrive at a good conclusion quickly and efficiently. Unlike human expert, ES adopts symbolic manipulation with heuristic inference procedure that is very close to human thinking process. For the ES to adopt this method, it makes use of the following approach:

Search Control: ES embarks on searching in a particular domain. Many techniques have been employed for this purpose. This includes pruning, branch and band, breadth-first search and so on. Because of the importance of search process, it is imperative to use good search control strategy in the ES Inference process.

Forward Chaining Method: In the development of an ES, various rules are put in place. There is therefore a need to check the condition part of the rule to determine truth or false value of such rule. If the condition is true, the action part of the rule is also true.

This process will continue until a solution is arrived at or a dead end is reached. This approach or method is being referred to as data driven reasoning.

2.7.2.3 Backward Chaining: Unlike the forward chaining, the backward chaining is used to backtrack from a goal to the paths that lead to a goal. Hence, it could be referred to as goal driven. It has been found highly applicable when all outcomes are known and not too large in term of size. (Olanloye, 2014).

2.7.3 Genetic Algorithm

This is a search algorithm. It has been used in this area of research to search for elements or minerals in a particular location. Data are not trained for further discovery.

It belongs to a field known as evolutionary computation. The processes of arriving at meaningful solution include:

(i) Survival of the fittest
(ii) Cross breeding
(iii) Mutation

In the process,

(i) A population of candidate solution is initialized (the chromosomes)
(ii) New generations of solutions are then produced making use of initial population. To produce these solutions, selection, crossover and mutation are used.
(iii) Next generation are then produced from fitness function which is used to evaluate the fitness of the newly evaluated solution.
(iv) The steps of generating solutions as well as the evaluation continue until acceptable solution is found.

2.7.4 Neural Network Method

The human brain consists of 100 billion closely interconnected single processing elements known as neurons. A simplified model of the neuron and their operation gave birth to ANN. Series of data which serve as inputs are used to train the network and hence produce the appropriate solutions. With newish data, the system is able to use its past experience to solve the problem. If Training or learning phase involved human intervention, it can be described as supervised learning or else it is an unsupervised learning.
They are very good at solving problem that are not prone to algorithmic solutions e.g. pattern recognition, decision support etc. It has the ability to handle previously unseen, incomplete or corrupted data.

It trains data and uses such data to predict the concentration of minerals in a particular area. The neural network method has been a useful method in this research area.

2.7.5 Wavelet Transform

The hyperspectral images will then be made to undergo wavelet transform. The wavelet transform is used in the developed system at pre-processing stage of the hyperspectral data / images / signal .The images or signals are transformed into mathematical functions

Wavelet analysis is a fairly recent analysis tool and the number of applications for which it has been used has expanded tremendously in the last 10-20 years. This expansion is indicated by the vast amount of publications on the topic – wavelets transform. Some of the most important aspects and the basic characteristics of wavelets in the context of this study will be explained in the following paragraphs.

Wavelets can be considered as an extension of Fourier analysis. With the Fourier transform, the signal is transformed into the frequency domain through the use of sines and cosines curves to represent the original function. The Fourier transform decomposes a signal in terms of frequency, whereas the wavelet transform decomposes a signal in terms of time-scale. The Fourier transform is more suited for stationary signals while the wavelet transform is more suited for non-stationary signals such as very brief signals and signal components with differing components at different scales). Since a spectral signature of mineral rocks can vary substantially with wavelength and do not follow a regular rhythmic trend over the spectral range, such as a normal sine wave, the wavelet transform will work very effectively to analyze reflectance spectra of mineral rocks in the developed system.

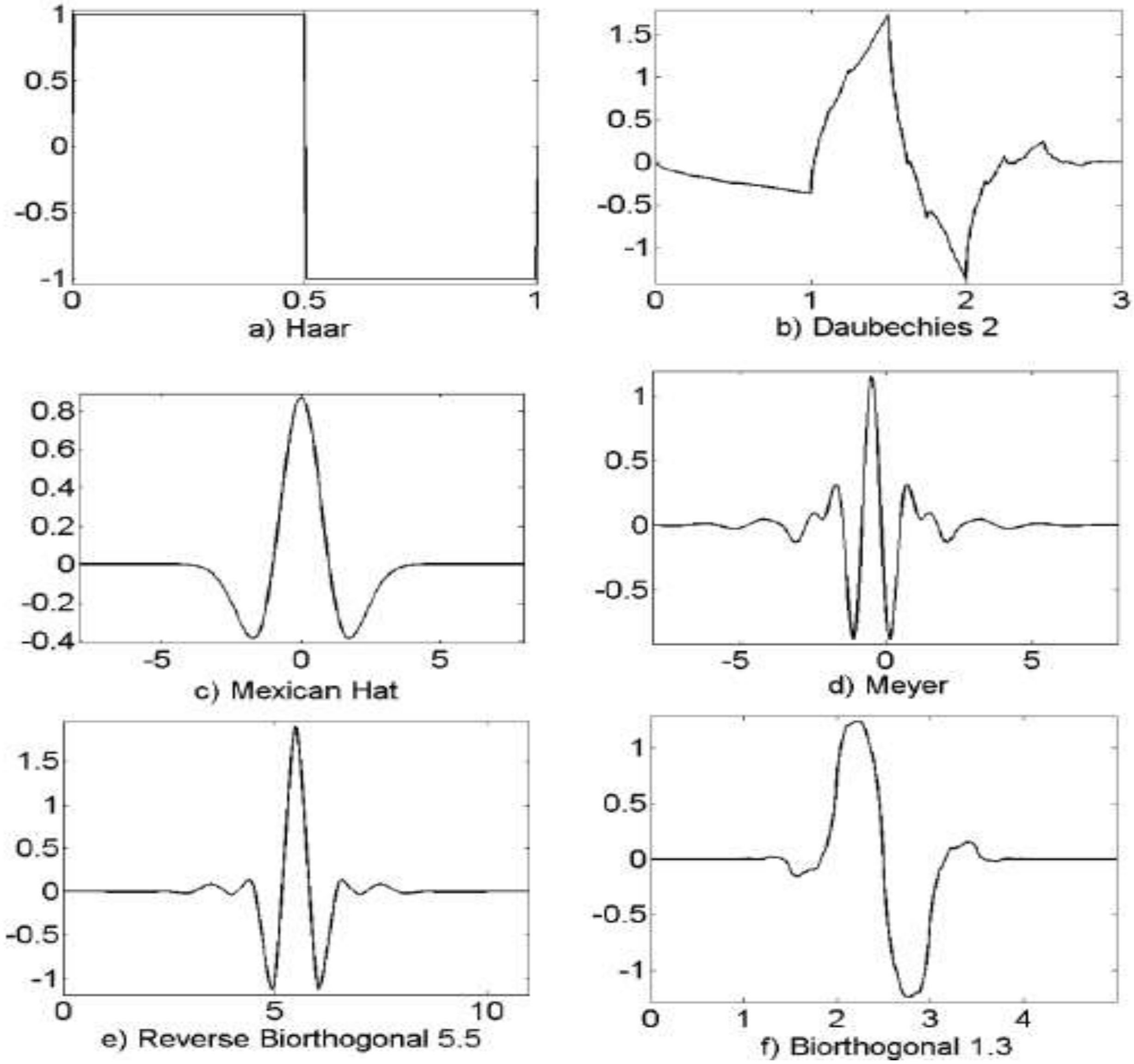


Figure 2.2: Examples of Wavelet Function from a Selection Wavelet Family (http://radio.feld.cvut.cz/matlab/toolbox/wavelet/ch01_31a.html)

The selection of wavelets portrayed in figure 2.2 shows some of the most recognizable wavelet functions, along with those used in this study. The selected wavelet functions are:

(a) The *Haar*wavelet, which is the oldest and simplest known wavelet function. The Haar wavelet is exactly the same as the Daubechies 1 wavelet.

(b) The *Daubechies 2* wavelet, which is named after one of the prominent wavelet researchers, Ingrid Daubechies He was one of the most recognizable person in the area of wavelets transform.

(c) The *Mexican Hat* wavelet, named after its distinguished shape, which is the second derivative of the Gaussian derivative density function.

(d) The *Meyer* wavelet, which is an infinitely regular orthogonal and symmetrical wavelet, named after another one of the founders of the field, Yves Meyer,

(e) The *Reverse Biorthogonal 5.5 (rbio5.5)* wavelet

(f) The *Biorthogonal 1.3 (bior1.3)* wavelet which will used in this study.

These wavelets are each part of a given wavelet family, consisting of other forms of wavelets with similar characteristics.

When any signal or time-series is analyzed using basic wavelet analysis, any one of these wavelet forms could be used as a basis for the analysis. Then, for this specific analysis, the selected wavelet is known as the *mother wavelet.* In the developed system, the concept of a mother wavelet is one of the fundamentals of wavelet analysis to be used.

2.7.5.1 Wavelet Characteristics and Thresholding

The continuous wavelet transform (CWT) is a function of two variable *W (a,b)* of a signal *f(λ)* given by:

$$W(a,b) = \int_{-\infty}^{\infty} f(\lambda)\psi_{a,b}(\lambda)d\lambda,$$

Where ………… (2.10)

$$\psi_{a,b}(\lambda) = \frac{1}{\sqrt{a}}\psi(\frac{\lambda - b}{a})$$

with *a* representing the width of the wavelet (*scaling* factor) and *b* the position of the wavelet (*shifting* factor).

In the developed system, there is a need to calculate the wavelet coefficients at every possible scale and for every possible position. This is computationally very inefficient, and an approximation of the process is needed, without losing any important detail.

The discrete wavelet transform (DWT) is such an approximation. In the DWT, a wavelet is shifted and scaled only by the discrete values. The scaling is most often by a power of 2, which is known as the *dyadic* length. That means that one uses wavelengths of the form

$$\psi(2^k\lambda + l) \qquad \text{…………. (2.11)}$$

where *k* and *l* are whole numbers . In this study, λ refers to the wavelength range between 393nm and 988nm.

Another characteristic of a wavelet function to be used in the developed system is that the sum of the area under any wavelet is zero. This means that it has a zero integrated area .Mathematically, this will be represented as

$$\int_{-\infty}^{\infty} \psi(\lambda) d\lambda = 0 \qquad \dots\dots\dots..(2.12)$$

The process of wavelet transform will lead to the next stage of the system. This stage is called *Thresholding*. Itis a technique used in the de-noising (removing unwanted signals) using wavelets. In the process, there is a certain cut-off value (the threshold), above which a certain rule apply, and below w hich a different rule apply.

By denoting the general thresholding rule as $\delta_\eta(x)$ where x is the input coefficient and η is a scalar or vector of parameter values, the operation of thresholding on the wavelet coefficient $o_t$is given by

$$\delta_\eta^{\mathrm{H}}(o_t) = \begin{cases} o_t \text{if} |o_t| > \eta \\ 0 \text{ otherwise} \end{cases} \qquad \dots\dots (2.13)$$

There are two types of thresholding used. These are:

Hard thresholding stipulates therefore that the coefficients above the cut-off level η are kept, and all the coefficients equal to or below this value, are set to zero.

Soft thresholding also sets the coefficients to zero that are smaller in magnitude than the threshold, but additionally all the other coefficients are pushed towards zero as well.

Shifting and Scaling of Wavelet

The top half of figure 2.3 shows how a wavelet runs through an example signal (*shifting*) from left to right. A set of coefficients are calculated for each such a run. The wavelet scale is increased to a bigger scale each time in the bottom half of figure 2.3, until the signal is decomposed at the different wavelet scales, from the finest details to the broad trends.

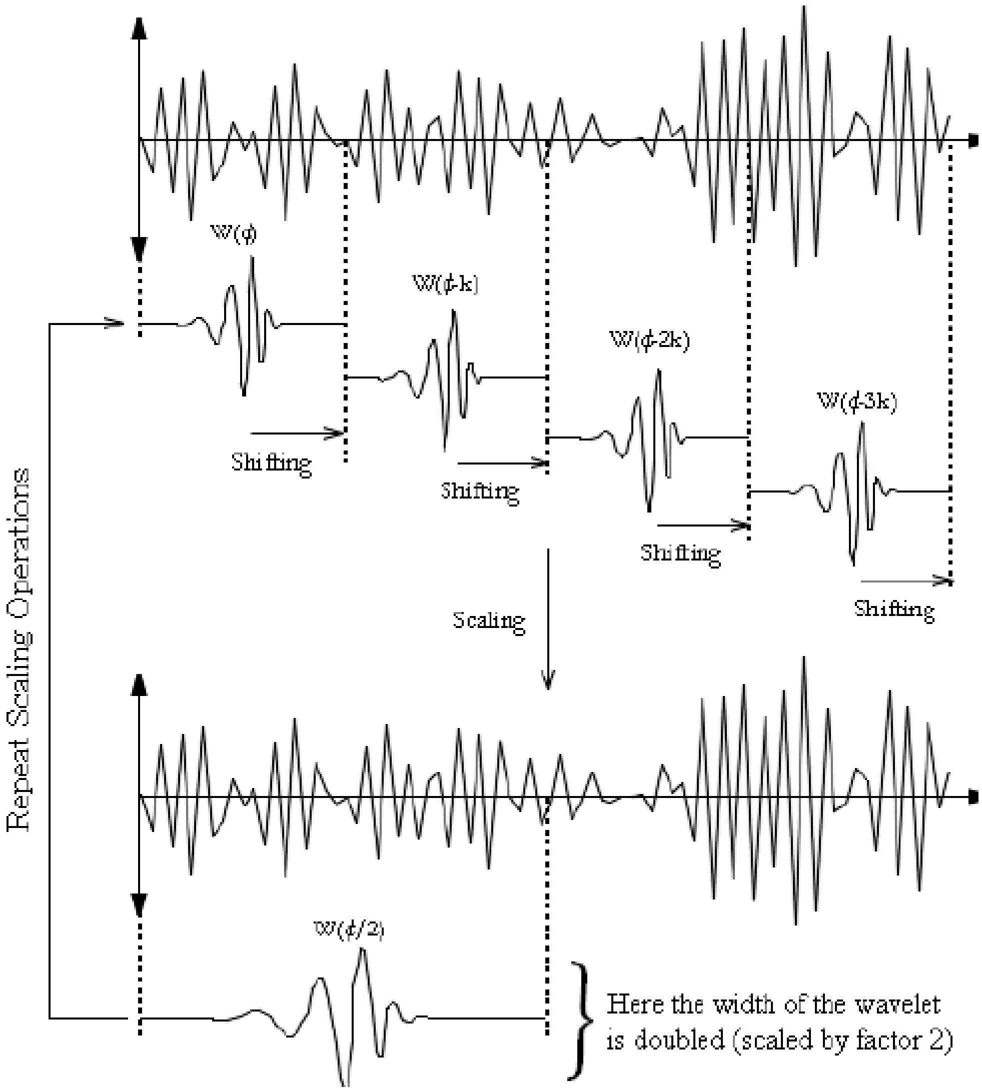


Figure 2.3: The Scaling and Shifting Process of the Discrete Wavelet Transform (http://www.wavelet.org/tutorial/wbasic.htm)

The number of times that the wavelet is stretched to different scales determines the *resolution* of that specific wavelet *decomposition*. This makes it possible to analyze a signal at different scales, from small wavelets, which emphasize the small detail, to big/ wide wavelets, which gives the general trend of the signal. Because of this, the wavelet transform is also sometimes referred to as a “mathematical microscope”.

2.7.5.2 Wavelet Decomposition and De-noising

Figure 2.4 shows the wavelet decomposition tree, which is how the original signal *f(λ)* is decomposed into approximation coefficient vectors *(Ai)* and detail coefficient vectors *(Di)* . The size of the boxes in Figure2.4 shows how the DWT halves the length of successive approximation and decomposition vectors. All the information in the original signal is contained in the approximation coefficient at a particular level plus the detail coefficients at that level plus previous levels. By using the inverse discrete wavelet transform (IDWT) the signal $f(\lambda)$ can be reconstructed without loss of information. Referring to Figure 2.3, $f(\lambda) = A1 + D1; f(\lambda) = A2 + D2 + D1; f(\lambda) = A3 + D3 + D2 + D1$. A summary of all the equations for the approximation coefficients and detail coefficients are obtained.

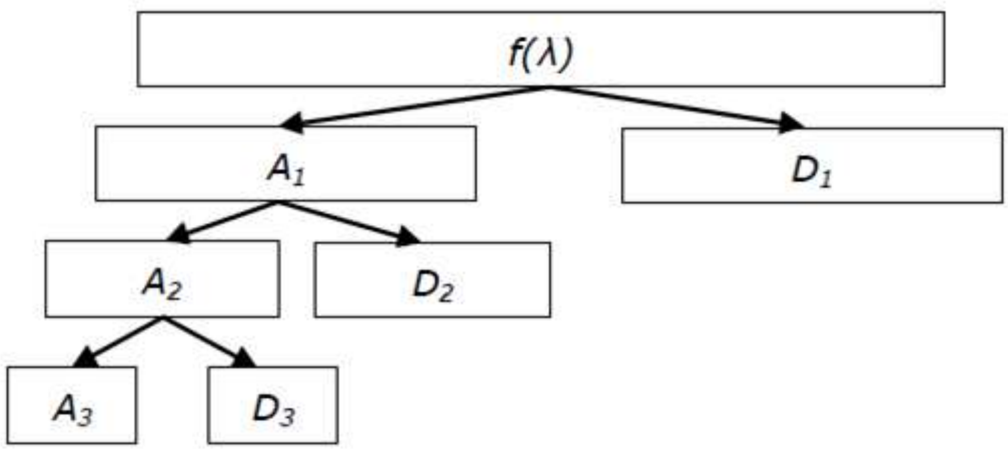


Figure 2.4: Multilevel Wavelet Decomposition Tree

Figure 2.5 shows the processes of scaling, shifting and decomposition from a different perspective, and how the wavelet coefficients can be used to de-noise a signal.

The basic de-noising procedure as illustrated in Figure 2.5 consists of three steps:

1) *Decompose the signal:* Choose a wavelet and its decomposition level.

2) *Set the threshold:* Set the threshold for the detail coefficients at a specific level.

3) *Reconstruction of the signal:* Reconstruct the signal from all the coefficients that fall within the selected threshold.

2.7.5.3 Similar Example

Figure 2.5a shows the original noisy vegetation reflectance spectrum used in this example. In Figure 2.5b, the vegetation reflectance spectrum is decomposed into its wavelet coefficients, by the DWT of the rbio5.5 wavelet, to the 5th resolution-level. The five detail coefficient vectors (D1-D5) and one approximation coefficient level (A5) are shown in Figure 2.5b, as these are all the coefficients that are needed to re-construct the original signal. Figure 2.5c displays the remaining coefficients after hard thresholding is applied. The threshold was set to η = level D4, so that all the detail coefficients from level D1 to D4 was set to zero. To reconstruct the signal again, the inverse discrete wavelet transform (IDWT) is applied to the selected coefficients to produce the de-noised signal in Figure 2.5d.

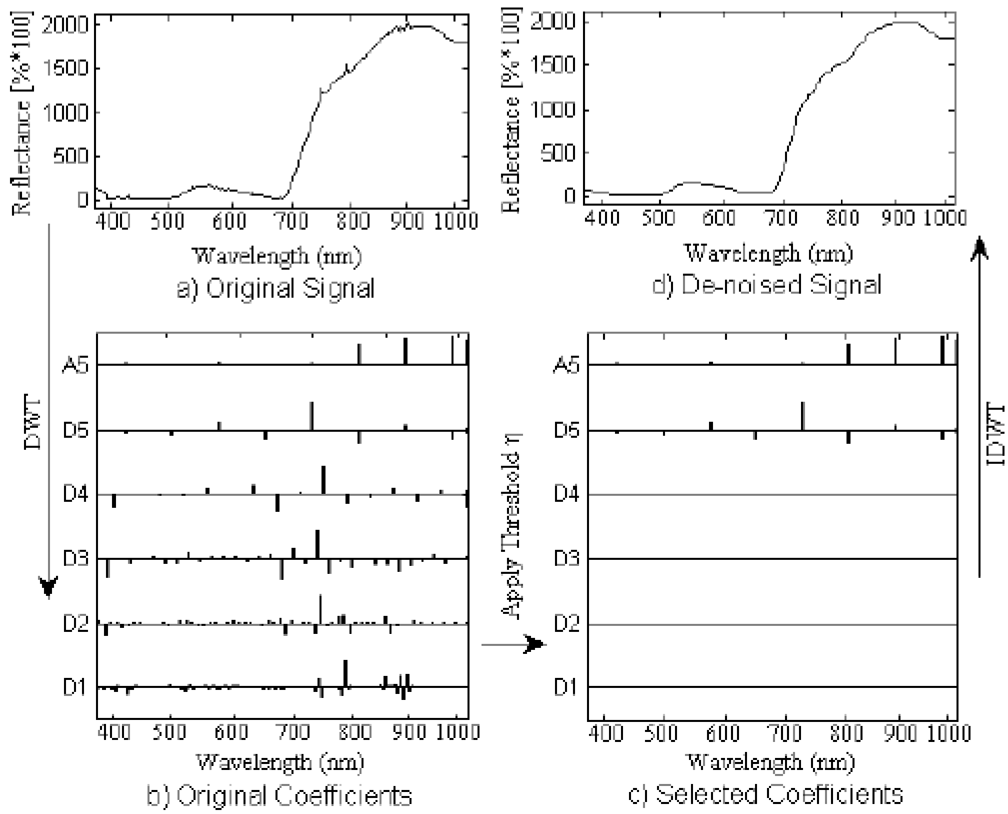


Figure 2.5: An example of how to de-noise a Signal Using Wavelets

In this example, the rbio5.5 wavelet was used, with a) the original signal, b) the original wavelet coefficients at level 5 decomposition, c) the coefficients that are selected after threshold η was applied, and d) the de-noised signal that is reconstructed from the selected coefficients. Figure 2.6 explains the image of the de-noising signal.

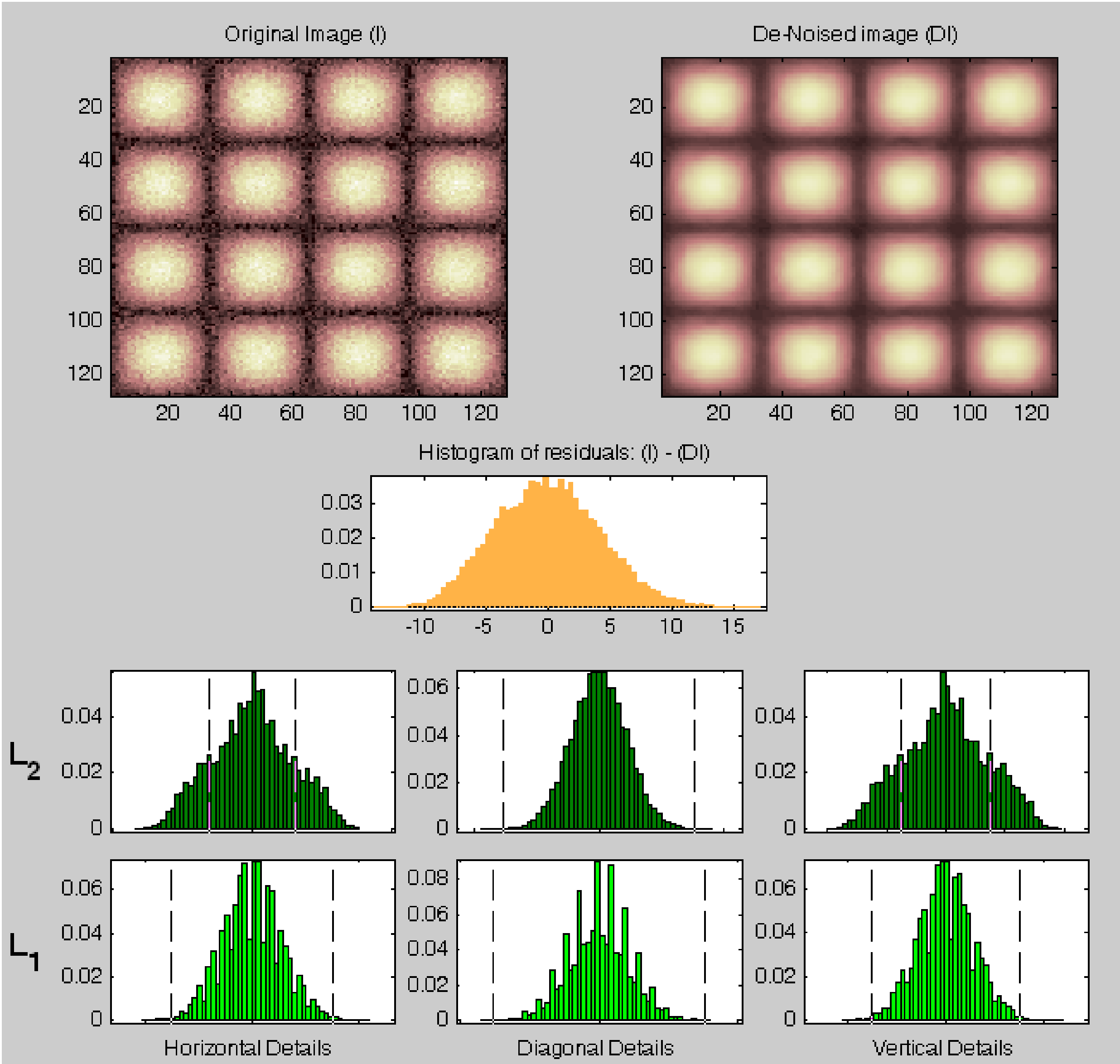


Figure 2.6: An Example of Image Denoising with Wavelet Transforms (http://www.mathworks.com)

The approximation coefficient obtained in the process of thresholding/denoising will now serve as an input vector for ANFIS.

2.7.6 Kohonen's Self-Organizing Map (KSOM)

According to John (2002), Teuvo Kohonen from Finland was the first to demonstrate how systems could be built to organize input data without being supervised or taught in any way. He studied that topological mappings of sensory and motor phenomena exist on the surface of the brain. The system was able to perform mapping of an external signal space into the system's internal representational space, without human intervention. He called this process a self-organizing feature map and showed how it could be performed by a neural network. Similarities among patterns are mapped into close relationships on the competitive layer grid.

Generally, Kohonen's later publications in 1995 and 2001 are regarded as the major references on SOM. Kohonen's description is "it is a tool of visualization and analysis of high-dimensional data". Additionally, it is useful for clustering, classification and data mining in different areas.

SOM is an unsupervised learning method, the key feature of which is that "there are no explicit target outputs or environmental evaluations associated with each input". During the training process, there is no evaluation of correctness of output or 'supervision'.

First, it is different from other neural networks, and it only has two layers which are input layer and output layer (or called competition layer) respectively. Every input in input space connects to all the output neurons in the map. The output arrangements are mostly of two dimensions. The Figure 2.7 shows below conventional 1D and 2D arrangements

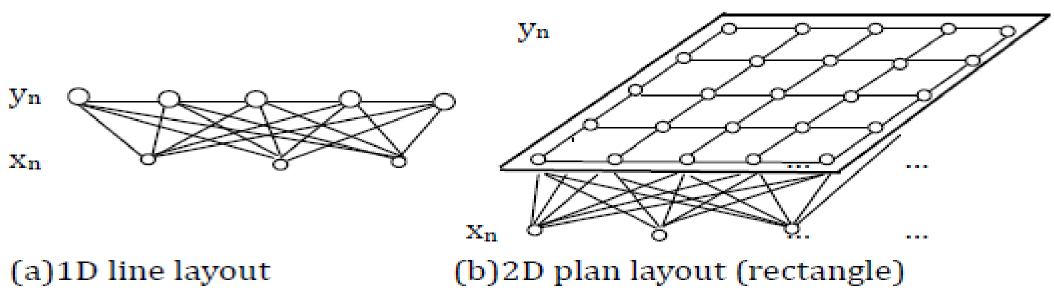


Figure 2.7: Conventional 1D and 2D Arrangement

In figure 2.7, $\mathcal{X}n$ represents the input neurons in the input space, $\mathcal{Y}n$ represents the outputs in the output space. Figure 2.7a shows a one dimensional arrangement in the form of a line layout. Figure 2.7b shows a two-dimensional arrangement in the form of rectangular layout. The Figure 2.7 shows that compared to general NN, SOM has no hidden neurons and the discrete layout of the inputs map to output space is a regular arrangement. Besides the rectangular layout, 2D SOM also has the form of hexagonal arrangement.

Next, the main process of Self-Organizing Maps (SOM) is introduced generally. The process is made up three main phases which are **competition, cooperation and adaptation**.

Competition: The output of the neuron in self-organizing map neural network computes the distance (Euclidean distance) between the weight vector and input vector. Then, the competition among the neurons is based on the outputs that they produce, where *i(x)* indicates the optimal matching input vector *x*, the formula can be represented:

$$i(x) = \arg min_j \left\| x - w_j \right\|, \quad j = 1,2, \dots, l \dots \dots (2.14)$$

In formula above**, *x***is the input vector,*wj*is the *jth*neuron's weight vector. It uses "Nearest neighbor search", which is interpreted as proximity search, similarity search or closest point search, consists in finding closest points in metric spaces. The neuron *j* which satisfies the above condition is called the "winning neuron".

Cooperation: The winning neuron is located at the centre of the neighbourhood of topologically cooperating neurons. The winning neuron tends to activate a set of neurons at lateral distances computed by a special function.

The distance function must satisfy two requirements: 1) it is symmetric; 2) it decreases monotonically as the distance increases. A distance function *h(n,i)* which satisfies the above requirements is Gaussian:

$$h(\, j, i) \; = \; exp(- dj, i2 \, / \, 2\sigma 2 \,) \qquad \dots \dots . (2.15)$$

In equation 2.15, *h(j,i)* is the topological area centred around the wining neuron *i*. The *dj,i* is the lateral distance between winning neuron *i* and cooperating neuron *j* and σ is the radius influence.

Adaption: it is in this phase that the synaptic weights adaptively change. Since these neural networks are self-adaptive, it requires neuron *j*'s synaptic weight *wj* to be updated toward the input vector *x*. All neurons in the neighbourhood of the winner are updated as well in order to make sure that adjacent neurons have similar weight vectors. The following formula state the weights of each neurons in the neighborhood of the winner are updated:

$$wj = wj + \eta h(j, i) * (x - wj) \qquad \dots . . (2.16)$$

In equation2.16, η is a learning rate, *i* is the index of winning neuron, *wj* is the weight of the neuron *j*. The *h(j,i)* function has been shown in equation 2.15.

These three phases are repeated during the training, until the changes become less than a predefined threshold. Figure 2.8 illustrates the flowchart for the process of updating weight for cluster unit. Again figure 2.9 shows segment of unsupervised learning algorithm. Figure 2.10 and 2.11 shows the cluster processing and adaptation of weight in KSOM respectively. Figure 2.12 explains the KSOM flowcharts.

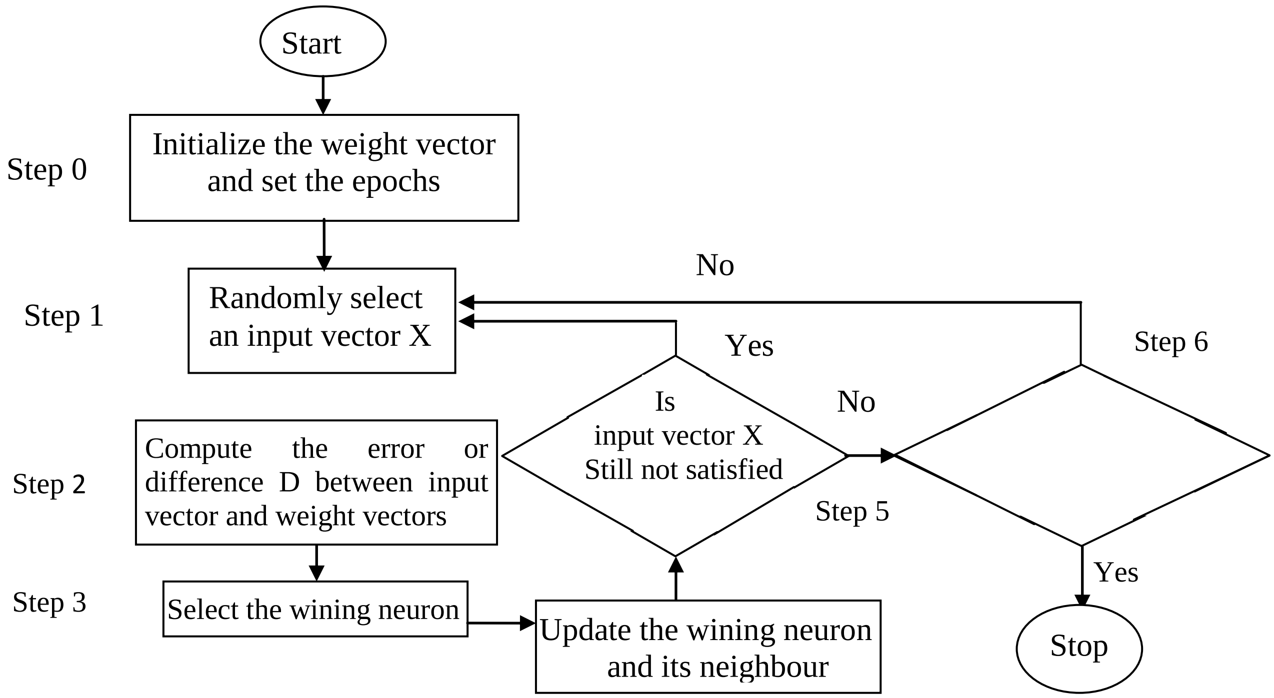


Figure 2.8: Flowchart for the Process of Updating Weights for Cluster Units

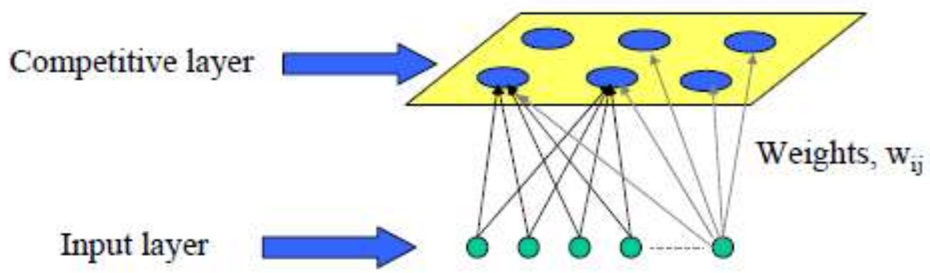


Figure 2.9: Segment of Unsupervisory Learning System (KSOM)

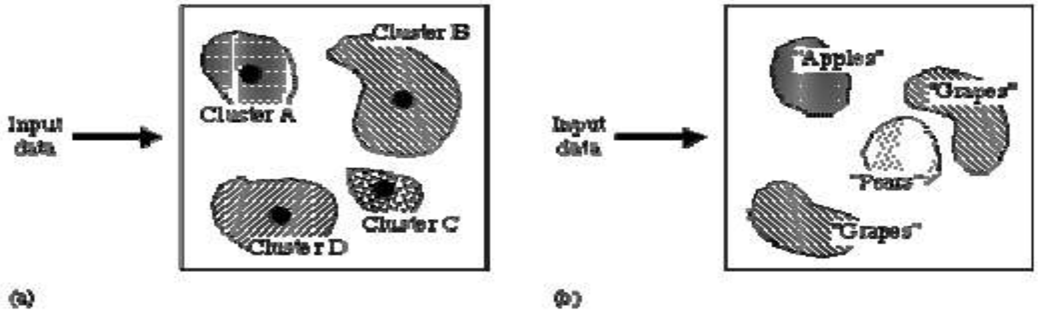


Figure 2.10(a, b): Cluster Processing Using KSOM

(a) By observing the input patterns, KSOM reorganizes them by clustering similar patterns into groups

(b) Next labeling is done for the Recall stage

The KSOM is an example of an unsupervised learning ANN.

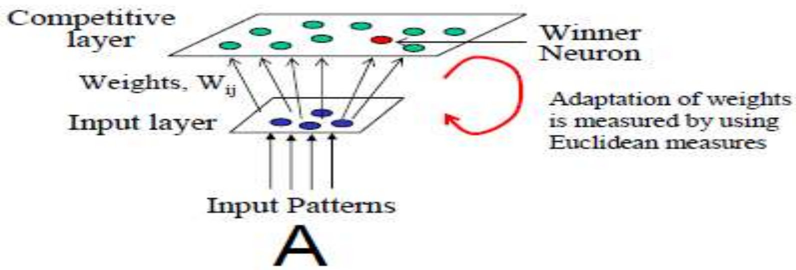


Figure 2.11: Adaptation of Weight in KSOM

Basic Principles of the KSOM

The KSOM neural network is basically a single-layer feed forward network.

When an input pattern is presented, each unit in the 1st layer takes on the value of the corresponding entry in the input pattern.

The 2nd layer units then sum their inputs and compete to find a single winning unit.

SIMPLE KSOM FLOWCHARTS

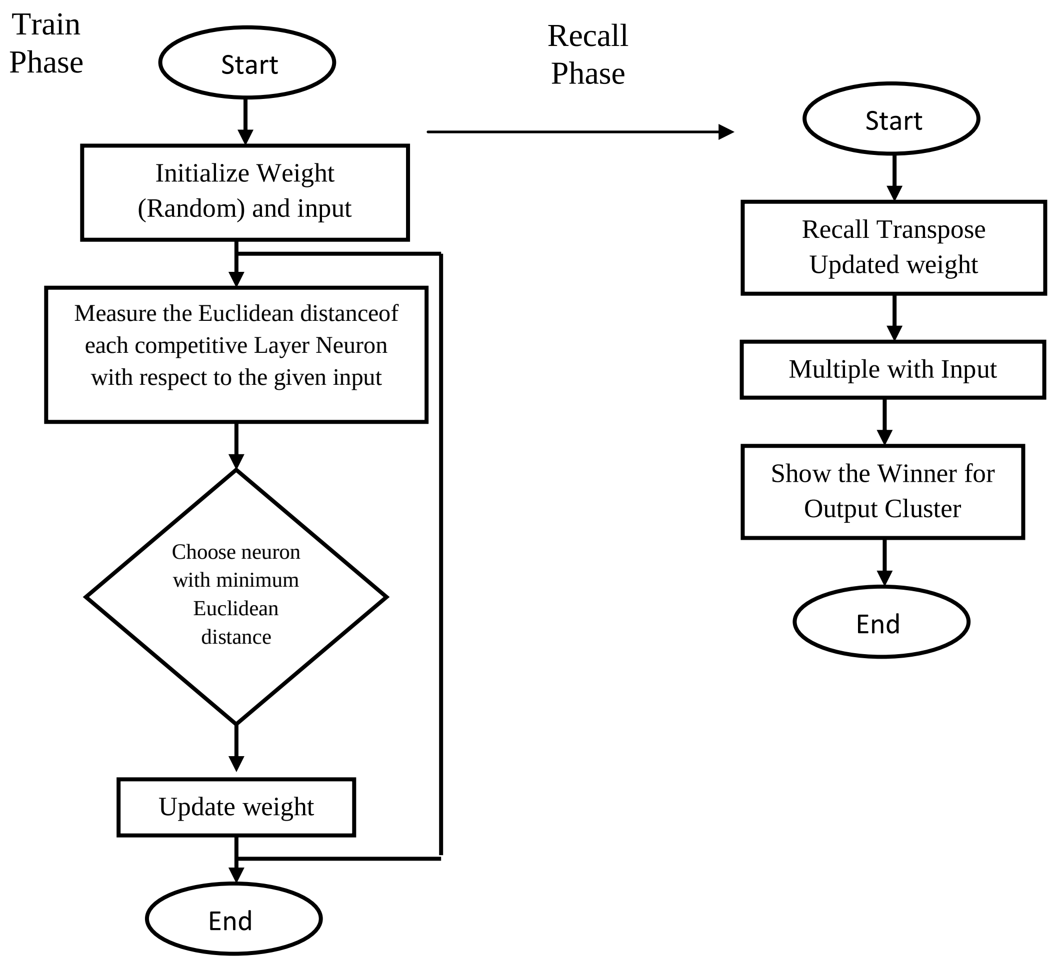


Figure 2.12: The KSOM Flowchart

CHAPTER THREE

3.0 SYSTEM ANALYSIS AND METHODOLOGY

3.1 THE EXISTING SYSTEMS

In the area of mineral prospecting, there have been different types of system that have been developed by various researchers and different types of methods or techniques were used by different researchers. Some of these systems are presented as follows:

(i) A system called a rule based expert system was developed for mineral identification. The idea is that the human expert is programmed into machine in the form of an artificial intelligence. The physical properties of the minerals were used as the basis for their classification or identification. This serves as the knowledge domain of the system. The type of inference engine developed is a rule based inference engine. The system was implemented using Visual Basic.

The expert system is divided into 3 parts. These are:

The knowledge base:- Consisting of the knowledge drawn or obtained from the field of the expert.

An Inference Engine: - This is a subsystem that is directed through knowledge base rules to manipulate the knowledge so as to draw inference from it.

A User Interface: - This is the mechanism through which non expert accesses the knowledge of the expert.

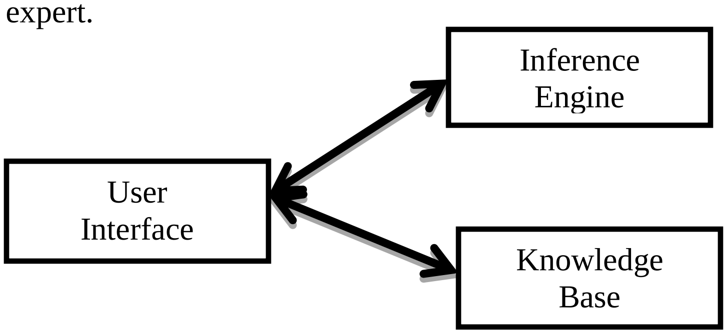


Figure 3.1: Main Parts of an Expert System

The system made use of the production rules as its knowledge base. The rules occur in sequences and are expressed in the form of $If(<(Condition)>, then <(Action)>)$. This means that if conditions are true, the system will proceed to execute the specified actions. But, if the conditions are not true, then the actions will not be executed.

When rules are executed by the inference engine, actions are executed if the information supplied by the user satisfies the condition in the rule. Conditions are expressions involving attributed connector “AND”. A sample of the rule used in the system is:

If

Rule 1 is found in the dbase *Rule2*

Then

Display mineral name

In the system, Rule 1(R1) is the information supplied by the user and Rule 2(R2) is the rule in the knowledge base for a particular mineral. The system was controlled in such a way that no two mineral share the same rule since every mineral has a unique attribute value.

As shown in figure 3.1, the heart of the system is the inference engine and the knowledge base behaves as the brain of the system. The inference engine used two different methods. These are forward and backward chaining. The inference engine executes action when conditions given are true. This involves assigning values to attributes, evaluating conditions and checking to see if all the conditions in a rule are satisfied.

A general algorithm for this system is stated below

$\boldsymbol{While}$ Values for attribute remain to be the input, Read values and assign to attributes and evaluate conditions for rules whose conditions are satisfied.

In the system, the rule base of the inference engine is stated as follows:

Attribute: $x_1,\ x_2, \dots, x_{n1}$

Condition: $C_1,\ C_2, \dots, C_{n2}$

Rules: $R_1,\ R_2, \dots, R_{n3}$

Actions: $A_1,\ A_2, \dots, A_{n4}$

The system only executes an action when a rule containing it is fired and a rule is executed only when all of its conditions are satisfied.

Advantages: This system can complement the efforts of the experts in the area of mineral identification. The system can combat loss of vital knowledge through the death of a human expert. Promotes effective teaching and learning of expert system. It minimizes the problem of scarcity of experts and reduces the cost required in mineral identification.

Disadvantages: It depends solely on the knowledge of the expert which might not be readily available. It depends solely on the database which needs to be updated from time to time.

(ii) Similarly, we have another system developed for Optimizing the Egyptian Coal Flotation using an Artificial Neural Network (ANN). In this system, back propagation Neural Network (NN) is used for optimizing a coal flotation process. The optimum value of flotation time, collector dosage, frother dosage and flotation cell impeller speed are determined by ANN.

The training of the NN is based on back propagation algorithm which basically involves three stages:

(i) The feed forward of the input training pattern
(ii) The calculation and back propagation of the associated error
(iii) The adjustment of the weight.

The number of neurons in the output layer was fixed. The recovery and grade have positive value between 0 and 100. The NN architecture and the inter connection of the layers are shown in figure 3.2.

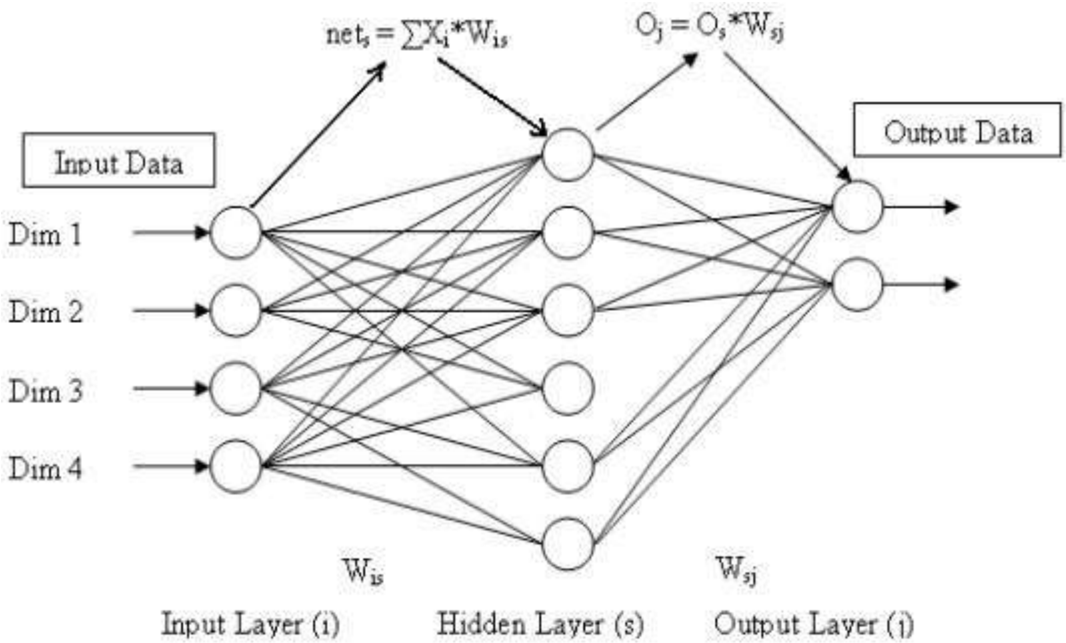


Figure 3.2: Supervised BPNN Architecture

The system used Back Propagation Neural Network which was a generalized least square algorithm which minimizes the mean square error between the network output and the target output.

Data entered are multiplied by connection weights and this determine the net input in the hidden layer

$$Net = \sum X_i W_i \qquad \ldots\ldots (3.1)$$

Where X_i is a vector of input

W_i is matrix of the connection weight from ith input layer unit to jth hidden layer unit.

And to transform the data from the hidden layer to output layer unit, sigmoid function is used as:

$$O_s = \frac{1}{[1 + exp^{-\lambda .net}]} \qquad \text{... ... (3.2)}$$

Where O_s is the output from jth hidden layer unit and λ is a gain parameter which controls the connection weight between the hidden layer unit and the output layer unit.

Output from the hidden layer unit is multiplied with connection weight to produce jth unit in the output layer

$$O_j = O_s \,. W_{sj} \qquad \text{... ... (3.3)}$$

Where O_j is the network output for jth output unit and $W_{sJ}$is the weight of the connection between 5th and jth output.

An error function

$E = \frac{1}{2}\sum_{j=1}^{c}(T_j - O_j)^2$ Was defined

where T_j is the target output vector

$O_j$is the network output vector

$c$is the number of classes

E is then compared with EL. If $E < EL$, the network training is stopped else E is sent back to the hidden layer through back propagation. The connection weight continues to update itself through several iterations.

The back propagation and the adjustment is explained as follows:

$$E_j = O_j \,. \left(1 - O_j\right). E \qquad \text{... ... (3.4)}$$

At each unit, the error vector is computed as:

$$E_s = O_s \,. (1 - O_s). \sum_{j=1}^{j=c} O_j - E_s \qquad \text{... ... (3.5)}$$

The system then computes the net error:

$$E_{sj} = O_s \,. E_j \qquad \text{... ... (3.6)}$$

The error in connection weight between hidden layer and input layer can be determined as:

$$E_{is} = f_{in} \,.\, X_i \,. f_s \qquad \text{... ... (3.7)}$$

Where f_{in} is the momentum factor which controls the connection between the hidden layer and the input layer units.

So far, the error vector is made available; the next iteration will take care of weight updating

$$(W_{is})_{new} = (W_{is})_{old} + E_{is} \qquad \text{... ... (3.8)}$$

λ, which is the gain parameter is updated as

$$\lambda_{new} = \lambda_{old} + L_{R\ .\ E_s} \qquad \text{... ... (3.9)}$$

Where L_R is the learning rate which control the time of the learning process. The process continues until the convergence is achieved and adjusted weights are obtained.

Advantages: The BPNN is trained automatically and validated with flotation results.

Disadvantages: When the number of neuron is too large, the network becomes heavy and complex. This creates the problem of overfilling.

(iii) Another type of intelligent system made use of Polynomial Neural Network (PNN) .The system is used in the area of Mineral Prospectivity Analysis in a GIS environment. The system was developed for analysis of mineral prospectivity and it was able to predict deposit and barren cells.

PNN is a flexible NN whose topology is not predetermined but developed through learning. The type of method adopted for their design is group method of data handling. Different regression values are computed for the input variable and the best for survival is chosen.

More layers are built based on the termination criteria which continue until the network stop getting better. This penalized the model from becoming complex and in turns prevents overtraining.

The data used to implement the system consist of 248 cells. Out of 248 cells, 147 were used for training and the remaining 81 for testing. This is shown in table 3.1

Table 3.1: Sample of Training and Testing Data set

Training Data Set			Test Data Set		
Deposit	Barren	Total	Deposit	Barren	Total
82	102	184	35	46	81

Both the training and the testing data consist of barren deposit. A number of neural network with 10-input and single output with different model complexity were trained.

Going by the result produced by the system, it can be established that PNN is not as good as BPNN in case of training set of data. But when tested on an independent test data set PNN is better than BPNN. The system was able to identify deposit and barrel location for the exploration of minerals.

Advantages: It is highly capable to determine the number of nodes and hidden layers. It also has shorter training time. The type of architecture involved is a flexible neural type and its topology is not predetermined but developed through learning.

Disadvantages: Many neurons are involved and the higher the number of neurons, the more complex the network.

(iv) Again, we have a system that made use of Multiple Layer Artificial Neural Network K-fold cross validation. The system used AI for classification of minerals based on colour values of mineral. A feed forward Multiple Layer Perception Neural Network (MLPNN) is one of the popular models.

A feed forward MLPNN trained with back propagation algorithm is quite good for classification and therefore was adopted in the development of this system. The accuracy of the system using ANN was between 90.67 and 97.62%.

For the purpose of collecting data, a digital camera and conventional microscope was used. The basic components of the system are as shown in figure 3.3 below:

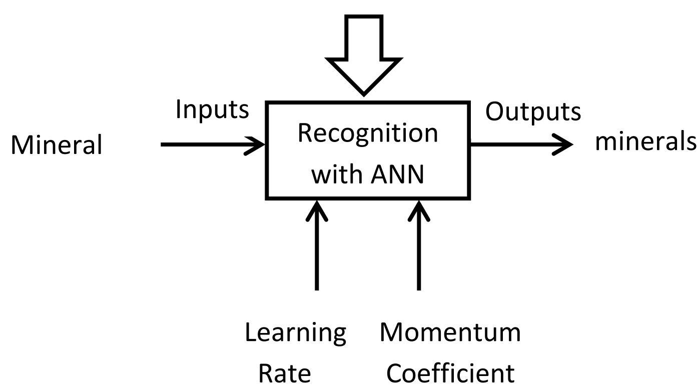


Figure 3.3: Basic Components of the System

In MLPNN, the input I_j is the summation of the weight W_{ij} and the input signal x_ii.e $I_j = \sum W_{ij} \,.\, x_i$ for the output y_i

$$y_i = f(\sum W_{ij} \,.\, x_i) = \mathrm{f}(I_j) \qquad \text{... ... (3.10)}$$

Where f is the activation function that is necessary to transform the weight sum of all signal onto a neuron. For training of the system, back propagation algorithm is used. In BP algorithm, error is calculated as the sum squared differences between the desired value and the actual value.

$$E = \frac{1}{2}\sum(yd_j - y_j)^2 \qquad \ldots\ldots(3.11)$$

Where $yd_j$is the desired value of output neuron j and y_j is the actual output of that neuron. For each iteration, each weight is adjusted to reduce the value of E

In this system, the networks were trained from 1000 epoch to 10000 epoch with a step of 1000 epoch. The training of the network was based on colour parameter. A total of 6 input parameters were used in the ANN.

And in order to come up with a less expensive solution, several networks were constructed. The best results were obtained from a network which was designed as 3 layers with 6 neurons as input parameters.

Advantages: It enhances future enlargement of parameters of mineral data. With simple modification, it could be used to solve different real life problems.

Disadvantages: Large amount of data is required for the implementation of the system. The system can only identify minerals that have different colours.

(v) Fuzzy model for mineral potential mapping. The model is defined as follows:

If X is a set of n predictor maps

$X(i = 1\ to\ n)$ with r patterns or(classes) denoted generically by $X_{ij}(j = 1\ tor)$ then set $A_i(i = 1\ to\ n\ in\ X)$, containing favourable indicators for the target mineral deposit type can be defined as follows

$\tilde{A}_i = \{(X_{ij}, N\tilde{A}_i(X_{ij}))\ \ / X_{ij} \in X_i$Where $N\tilde{A}_i$ is the membership function for estimating the fuzzy membership value X_{ij} in the fuzzy set A_i.

The membership function $N\tilde{A}_i$ are of the following properties

1. $0 < (X_{ij}) \leq 1$
2. 0.5<$N\tilde{A}_i(X_{ij}) \leq 1$ where X_{ij} is a positive indicator of target mineral type.
3. $\mu\tilde{A}_i(X_{ij}) = 0.5 + +$ if and only if X_{ij} is a neutral of target mineral deposit type; and
4. $0 < N\tilde{A}_i(X_{ij}) < 5$ if X_{ij} is a negative indicator target mineral type

   $f = \sum_{i=0}^{n} \tilde{A}_i$Where it is a synthesized fuzzy set $\sum$is the fuzzy set operator containing favourable exploration target

Disadvantages: It is a model and not a developed system.

Advantages: The model can be developed into a system using different method of implementation.

(vi) Another type of system developed applied fuzzy Analytical Hierarchical Process (AHP) method to integrate geophysical data in prospect scale, a case study: Seridune Copper deposit. The developed system made use of fuzzy knowledge based method to integrate different geophysical dataset in other to prepare mineral prospecting map. The summary procedure of applying fuzzy method to prepare MPM according to the author is shown in figure 3.4 below

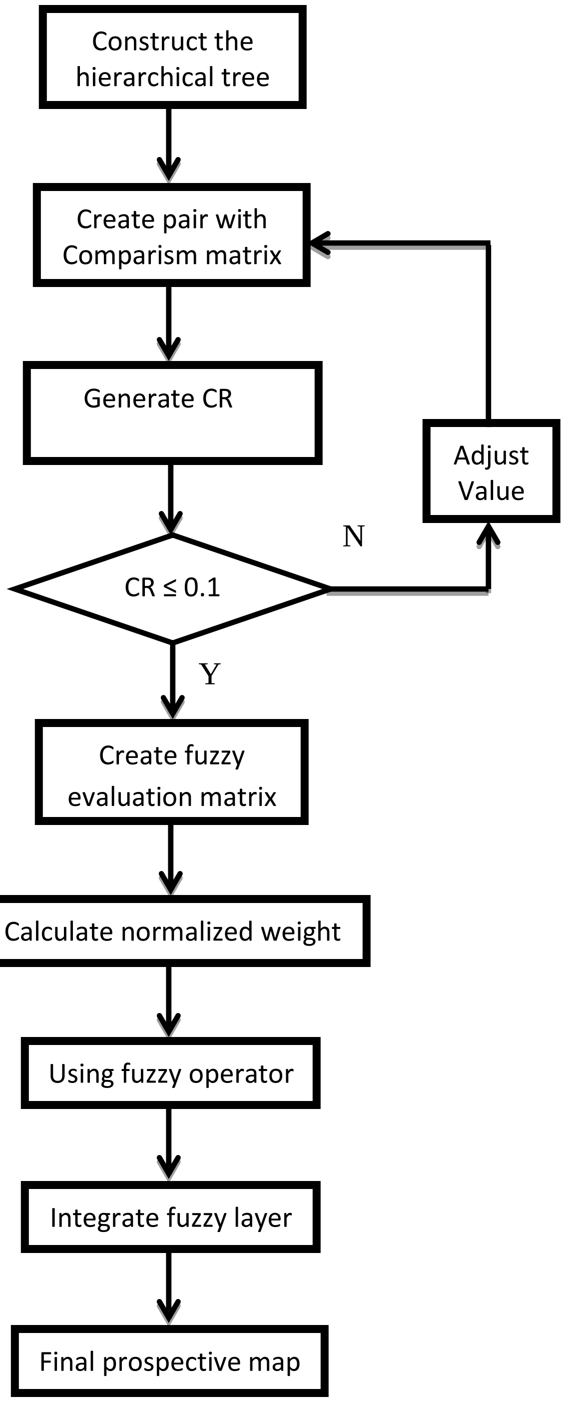


Figure 3.4: Procedure of Applying Fuzzy Method

The system made use of triangular fuzzy numbers. A fuzzy number in an R $(M \in m(R))$ is a triangular fuzzy number if the membership $\mu_m(x): \rightarrow [0,1]$ is equal to μ

Advantages: It makes use of fuzzy knowledge base to integrate various data layers and this reduces uncertainty in the operation of the system.

Disadvantage: The system is particular about identification of only one mineral (Copper) and not variety of minerals.

3.2 ANALYSIS OF THE PROPOSED SYSTEM

The new system is capable of reducing the large set (Size) of hyperspectral data to a reasonable size that can further be processed to obtain relevant information.

Though, the research work is applicable in the field of geoinformatics for mineral Prospecting, yet it could be used in the area of Land Topology, Soil, and Vegetation Identification. Hence, in the description of the system, the mineral represents any natural resources in the area being considered.

The developed system is a non-linear system. It is a non-linear system in the sense that the input data set and the output generated were made to relate with each other through a non-linear function. Hence, the mapping that exists between the input and output variable is a non-linear mapping. This is simply because the underlying mechanism to be modeled is inherently non-linear.

The system is to determine the classes of mineral and the exact type of mineral in each class. Knowing the exact type of mineral in each class, the system can estimate the possible quantity of mineral in each class. Again, it can be possible for the system to predict the likely novel mineral that are present in a given hyperspectral data

3.2.1 Modules of the Developed System

The system consists of seven major modules. These consist of input, characterization, clustering, unsupervised, supervised, novel and volume modules.

(i) Input module

The input module is required to read and load the hyperspectral data into the system. The data may be located in local data storage or in a networked repository. The data may be read in bulk or streams with appropriate staging, extraction, transform and load functions. The data should be read into an internal matrix data type for further processing. Also, the module should enable processing functions such as normalization, selection of bands, examination of spectrum for particular mineral and visualization of the data cube in general.

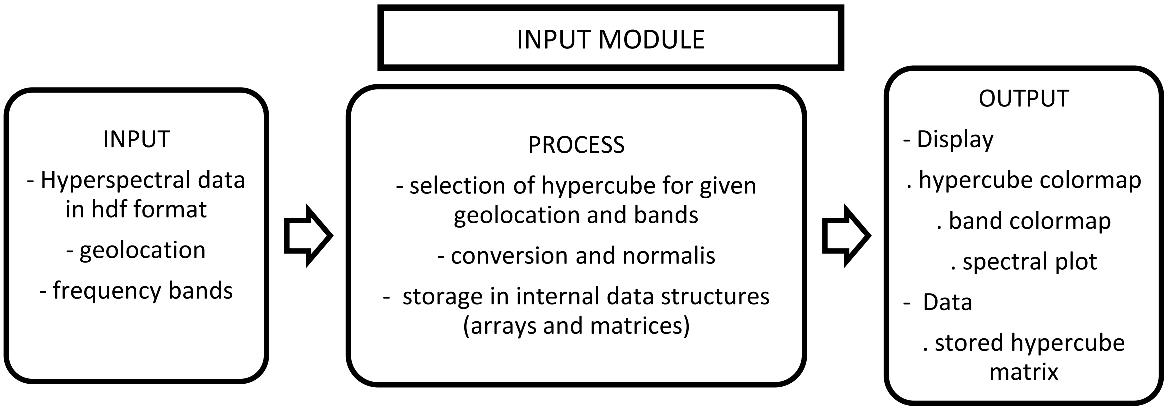


Figure 3.5: Structure of the Input Module

The input module presents a user screen that displays input options for selection of hyperspectral data in hdf format that we wish to work with. Thus it shall have function for viewing data files available locally or that can be downloaded from remote repositories. The data could be selected at various frequency bands.

It should input geolocation, present a visual display of the hyperspectral data for such location and select functions for frequency bands. The input module then loads the data into memory with system level data read function. The loaded data is converted to matrix representation and normalized for storage using internal data structure. After processing the system display hypercube colormap, band colormap, spectral plot and stored hypercube matrix. The structure of the module is shown in figure 3.5.

(ii) Data normalization

We normalize the data set to keep the data range between 0 and 1 to ease subsequent computation. This is obtained by dividing each of the data points by the maximum data point in a given set of data .The algorithm used to implement this is further explained in charpter4(system design).

(iii) Characterization module

Essentially this module is responsible for conversion of the spectrum for a given mineral to a form that can be used to characterize the mineral. The output is in form of map plot, ‘character’ image of the spectrum for the mineral. It should provide a visual plot of the map and store the characterization map in a matrix data type for further processing. This is explained in figure 3.6.

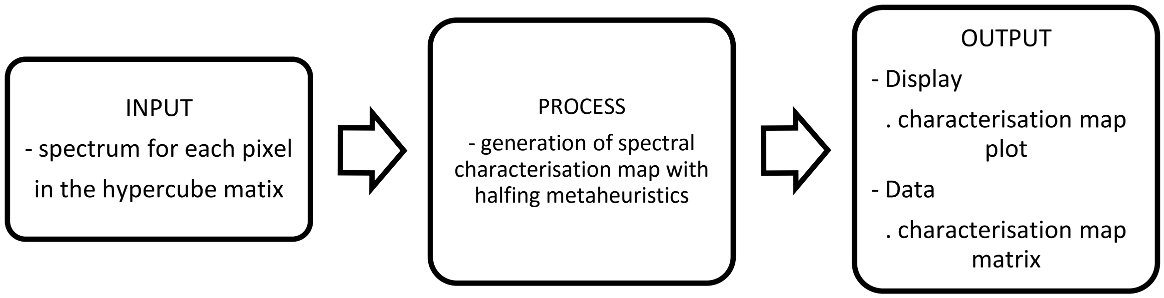
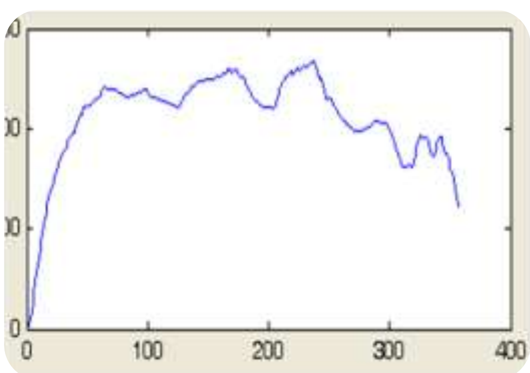


Figure 3.6*: *Structure of characterization Module

The module selects the spectrum data for particular mineral in the hypercube matrix and converts it into characterization map using halfing Metaheuristic. The module displays spectrum of minerals (3.7a) and characterization map with cluster centre figure (3.7b).



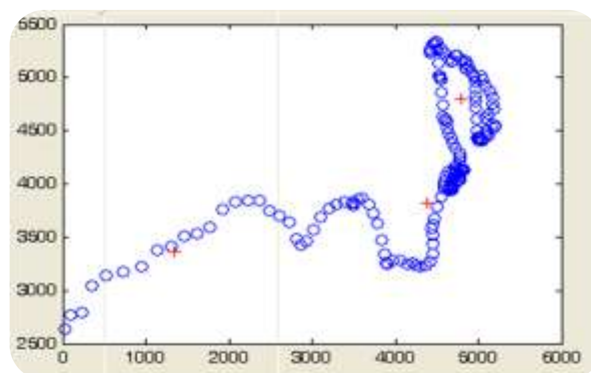


Figure 3.7a: Spectrum of the mineral

Figure 3.7b: Characterization Map

Halfing Metaheuristic Algorithm

Step1: The given data series is cut into halves of equal sizes.

Step2: The data in the first half is selected pointwise as horizontal coordinate and plotted against those in the second half as vertical coordinate, thus creating a series of point image to form the characterization map. The algorithm is shown in chapter 4.

(iv) Clustering module

The module can use suitable algorithm to extract features from the characterization map. Features that are invariants within certain error limits, such that mineral with the quazi-equal spectra that have the same set of features will be obtained. Thus, a clustering algorithm with probability classification capability is required.

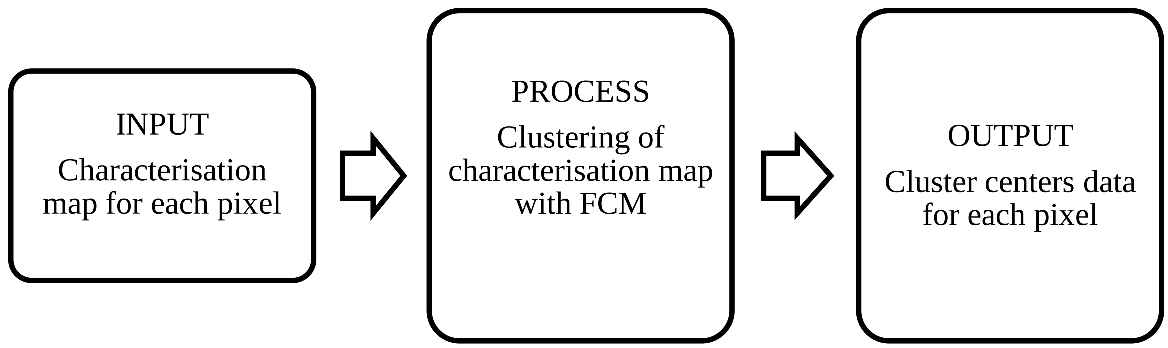


Figure 3.8: Structure of the Clustering Module

The type of clustering algorithm to be used should be the type where data point can belong to more than one set with fuzzy probabilities. Such probabilities are defined by membership functions. To achieve this, we modified Fuzzy c-means (FCM) data clustering algorithm where each data point belongs to a cluster to some degree that is specified by a membership grade.

From figure 3.8, we input the characterization map for each mineral. At the processing stage, the characterization map is clustered using modified fuzzy C means clustering algorithm. The clustering eventually produced the required cluster centre as output.

(v) Unsupervised learning module

The task of this module is to classify each mineral in the input matrix into certain number of classes that signifies the presence of certain type of mineral in the given area. The module will learn to classify the cluster center data obtained from the previous module into appropriate classes. After appropriate unsupervised training, the trained network should be able to recall the class to which a particular given mineral belongs based on the cluster center data for such mineral.

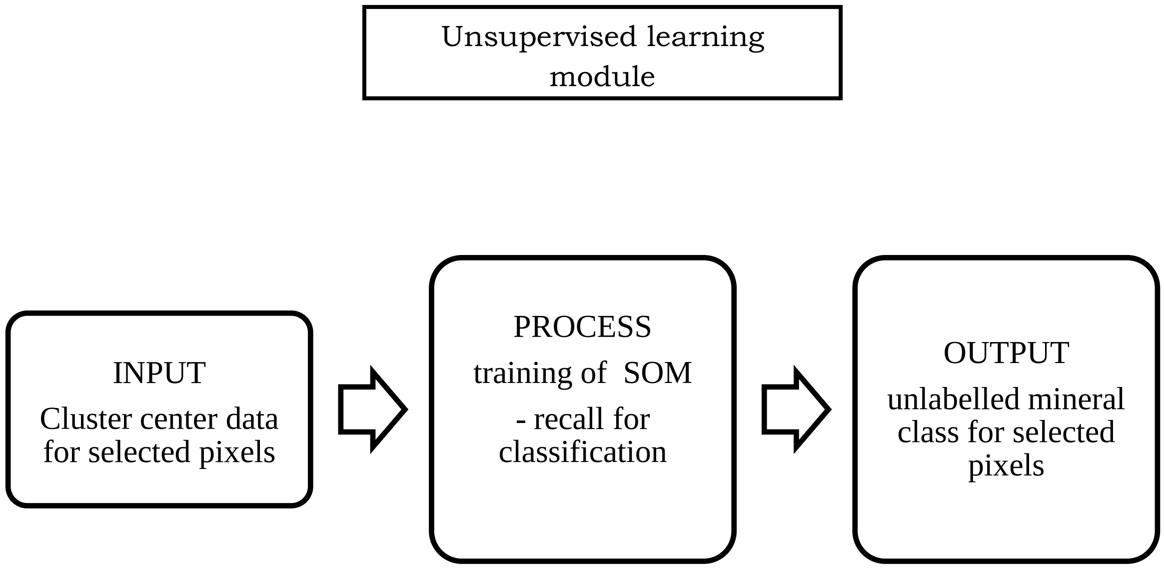


Figure 3.9: Structure of Unsupervised Learning Module

The module uses unsupervised learning algorithm to classify the cluster center data for mineral. It takes the cluster center data for selected mineral samples as input, process it through modified SOM and generate mineral classes(unlabelled mineral class) as output as shown in figure 3.9.

(vi) Supervised Learning Module

In this module, spectral library of known mineral is used to train the network to recognize different types of mineral that are present based on their cluster centers. This is achieved by making use of various rules. After successful training and testing, the algorithm links up and train unsupervised learning algorithm which in turn use the knowledge to identify the specific mineral in each of the classes it has earlier identified. This is one of the beauties of this research work.

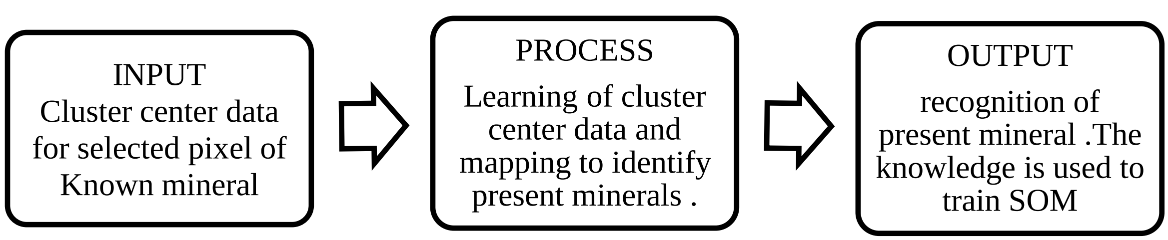


Figure 3.10: Structure of supervised learning

In this module, we modified hybrid Neuro-fuzzy learning algorithm, namely adaptive Neurofuzzy inference system, to recognize the name of a particular class of mineral in a given hyperspectral data. The input consists of known mineral. The processing stage is the learning stage which consists of training and testing of the data to identify the present mineral. At the output level, the system is able to acquire enough knowledge to recognize the name of mineral that are present in each of the classes. The knowledge is used to train SOM which in turn used the acquired knowledge to identify the name of specific mineral in each of the classes earlier recognized. This is explained in figure 3.10.

(vii) Reserve Volume Estimate and Novel Mineral

The module will use the network trained in the previous module to generate the potential map for a given location. It will use the generated map to estimate the reserve for a given mineral class by calculating the number of pixel in that class as a ratio of the total number of the pixel in that particular class to the total number of pixel in that location. In case the trained network cannot recall the class for a given mineral, for it has not encountered the mineral before, such mineral will be classified as novel. One after identification, the cluster center data for such mineral should be used to retrain the network so that it can recognize its occurrence in the future.

i.e. Reserve Volume Estimate = number of pixel in a class / total number of pixel in that location

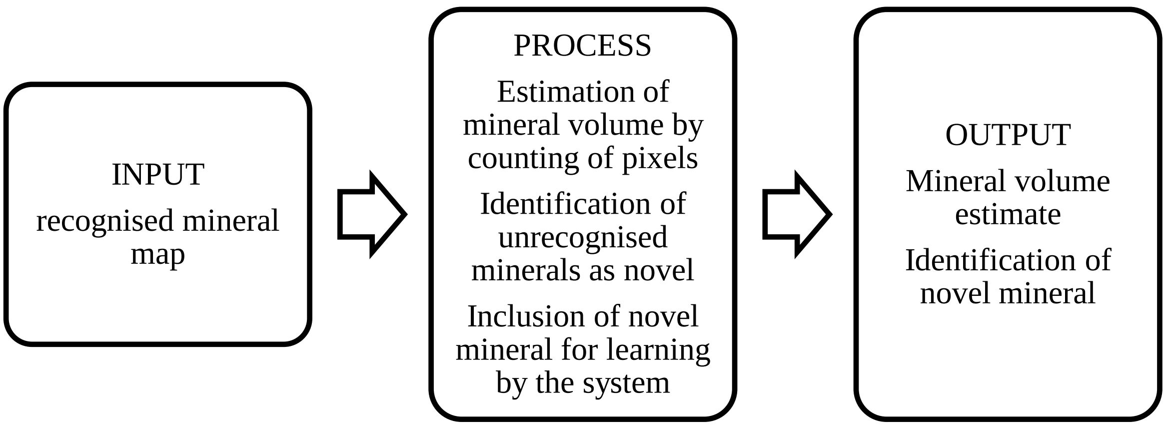


Figure 3.11: Structure of Reserve Volume Estimate and Novel Mineral

The input is the mineral map of recognized mineral. At the processing stage, the ratio of the number of pixel in a particular class to the total no of pixel in a particular location is calculated. The calculated ratio gives the estimate amount of mineral in that class. Again, when the system comes across a new set of data that is not part o its database, it signifies it as a novel mineral. Hence, at the output level, the knowledge acquired for mineral volume estimation and for the identification of novel mineral is transferred to unsupervised learning algorithm to process further the classes of mineral it has earlier identified. This is depicted in figure 3.11.

3.3 ADVANTAGES OF THE NEW SYSTEM

The developed system has the following advantages:

(i) The system should from time to time accommodate new problem solving rules. This makes the system to take appropriate decision at appropriate time.
(ii) The system is capable of analyzing itself in terms of behavior error and success.
(iii) Since the system is fully automated, it can learn quickly from large amount of data which further increases the efficiency of the system.
(iv) The system has the ability to generate a new knowledge. The system is not just learning from the given set of data but learns to apply the acquired knowledge to solve future problem.
(v) It has the ability to classify the given set of hyperspectral data into different classes such that data in each class are similar to each other and dissimilar from that of the other classes. The system is able to achieve this because of its ability to recognize the pattern of the data.
(vi) Having learnt from past data, it is possible for the system to name specifically the type of data or mineral that are present in the identified classes.
(vii) Through its level of intelligence, it can also recognize new set of data i.e. data set that are not part of its database.
(viii) The system through its intelligency carry out data reduction from larger size to an acceptable size that will be suitable for further processing.
(ix) The system will be of great assistance in solving some lingering geoinformatics problems.
(x) The interface was made so simple that will not demand for too much technical skill before it can be operated.

3.4 DISADVANTAGES OF THE NEW SYSTEM

Though, there are series of advantages that can be derived from the developed system, however, the system also has its own shortcoming which includes:

(i) It is developed to solve non-linear problems.
(ii) The system can only perform optimally when there is a large and sufficient data to train the system
(iii) The developed system is implemented with hyperspectral data. Hyperspectral data might not be readily available in some cases.
(iv) To be able to operate the system successfully, the user is expected to possess basic knowledge of computing

The high level model of the new system is shown in 3.16

3.5 JUSTIFICATION OF THE NEW SYSTEM

There are different types of intelligent systems that have been developed to solve real life problems. Literature reveals that enough efforts have not been made in the area of developing an intelligent system in the area of geoinformatics. Therefore, the developed system is an intelligent geoinformatics system that could be used to solve different types of geoinformatics problems. The beauty of the system is that it made use of hyperspectral data from the satellite to generate relevant information in the area of geoinformatics.

Furthermore, the system is an intelligent system which processes hyperspectral data by combining various AI algorithms. The combination of these algorithms will make the developed system better than the existing system.

The research work has introduced a new direction of processing hyperspectral data to obtain relevant information. Assuming we apply the system in the area of mineral prospecting, it will be possible for one to get names of the mineral in a particular location without leaving the bedroom provided the hyperspectral data of such location is made available on the internet.

Again, if there is a new type of mineral that cannot be classified with various features given in the ANFIS knowledge base, the developed system quickly indicates the presence of novel mineral which could be further investigated to detect the type of mineral present. Apart from detecting Nobel mineral, the developed system easily identify the location of the known mineral.

Though, Nevada is used as a case study, the system will be able to perform equally if supplied with relevant data (hyperspectral data) from any part of the world. Countries that have no hyperspectral data yet will still benefit from this system as soon as such data is available.

Many countries are endowed with one mineral or the other but most of such minerals wasted away undetected because the existing system are not sophisticated enough to detect such minerals. The developed system will detect such minerals thereby boosting the mining industry, provide more job opportunity for school leavers and increase at overall level, the standard of living of the country.

Finally, this is the first time an artificial intelligent principles will be used to develop an intelligent system that can be used to solve to geoinformatics problem.

The model diagram of the system is shown in figure 3.16.

3.6 RESEARCH METHODOLOGY

There are different types of methods that could be used in the design of an intelligent system. For the purpose of this research, we adopt Artificial intelligence approach which is an acceptable method for designing and developing AI system. In the process, the following stages are involved:

(i) System Study: We carried out problem identification and preliminary analysis. Again, we are also interested in detail study of the principles and techniques that govern the operational activities of the developed system.

An attempt was equally made to study the concept of knowledge base and inference engine using different types of rules. It was the knowledge base and the inference engine rule that is used in training and retraining of the dataset by both supervised and unsupervised learning algorithm.

(ii) Design: At the design stage, we ensure that the methodology provides a good knowledge representation in AI and is capable of building a good relation between the knowledge base and the various rules. So, the research considers:

  (i) Knowledge Representation:- This involves rule surface and rule based.
  (ii) Interface: - Forward and Backward Chaining. Forward Chaining which essentially involves data driven was used in this research work.
  (iii) Implementation: - The computational intelligence developed in this research work was implemented using R programming language and MATLAB in R scripts. We discuss this in detail in chapter 5.
  (iv) Testing and Evaluation: - The system was tested with available hyperspectral dataset. The system was able to identify some mineral that are almost the same with the available mineral in the area.

3.6.1 METHOD OF DATA COLLECTION

3.6.1.1 Data Extraction

Usually, hyperspectral data rare stored in HDF (hyperspectral data format) and may be available for direct download online in form of file. The size of the hyperspectral file varies depending on the size of the given site, spatial resolution and the number of bandwidth.

The spatial resolution may range from 50mm for older images to 10mm for newer images. Each spatial grid point is represented by a mineral in the image and the spectrum for a particular mineral will consist of reflectance values i.e. (0-1.0) for the number of considered bandwidth (wavelength ranging from 0.4μm to 2.5μm) above 300 for hyperspectral images.

Thus, the data consist of m x n pixel and k bandwidth. Thus, mathematically, the system should be able to read the given hyperspectral image into a 3dimensional matrix (hypercube).

Say: $hyperdata = input\ (m, n, k)$

The system should provide visualization of the ingested data in the form of hypercube (for the whole datasets), sliced image of each bandwidth for all pixels, and graph plot of the spectrum for each mineral as follows:

$hypercube => drawcube\ (hyperdata, m, n, k)$

$images => drawimage\ (hyperdata, m, n, k_s)$

$where\ k_s := 1..\ k_s$ provide interface for selecting a particular $k_s$bandwidth for viewing

$spectrums\ => plotgraph\ \ (hyperdata, m_i, n_j)\ \ where\ 1 < m_i < m$ and $1 < n_j < n$ provide an interface for selecting a particular $m_i$and n_j pixels for viewing.

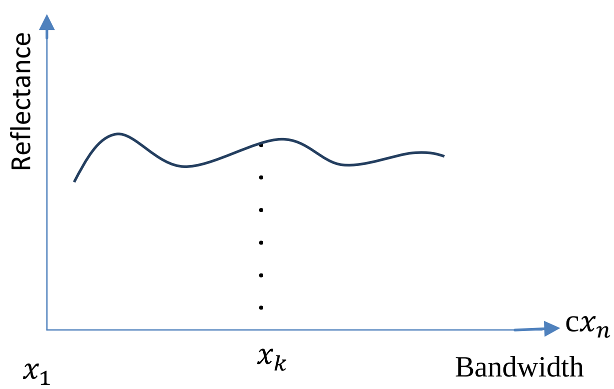
3.6.2 Data Reduction and Feature Extraction

The next stage is to extract features that can be used as predictors. The spectrum of each mineral in a given hyperspectral dataset consist of reflectance value for bandwidth that is more than 300. The high dimension of this spectrum makes its direct use as predictor impossible. Thus, it is necessary to find an approximate method or technique for reducing the dimension and extracting features that can be used to characterize the particular spectrum which will be suitable as input for classification and learning algorithm.

Methods in the literature such as principal component analysis etc. do not suffice for our purpose. Therefore, it became necessary to develop a new technique (a sort of Metaheuristic) that transforms a given spectrum into 2-dimensional characterization map as follows:

3.6.3 Characterization

The given spectrum in figure 3.12 is a line graph consisting of above 300 data points (reflectance values 0-1.0). This is illustrated in figure 3.14



$x_k: 1 \leq\ k\ \leq\ n$

Figure 3.14 Data Reflectance Valu

$where\ n\ is\ the\ number\ of\ bandwidth$

To transform the spectrum to a 2-dimensional characteri

the so called halfing algorithm which essentially plots half of the spectrum along one axis ($x-$ axis) against the other half along another axis ($y-$ axis) thus creating a characterization map for the given spectrum. Figure 3.15

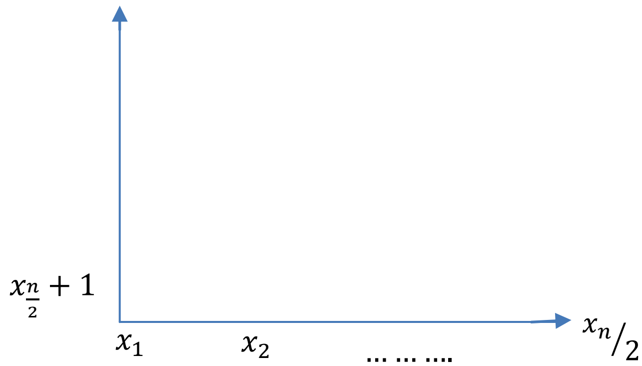


Figure 3.15 Characterization Map of the Spectrum

The obtained characterization map has many interesting properties and preserves the original information content, scales half of the spectrum against the other thus eliminating variation and error due to precision and disturbances during the data acquisition. Characterization maps obtained with halfing method display obvious visual features of the original spectrum. Now, we have a characterization map for a given spectrum from which we need to extract features that can be used as predictors or inputs for classification or learning algorithm.

3.6.4 Clustering

As usual, method for data summation and classification is clustering. During clustering, we set each point of the characterization map as belonging to some clusters with some degree of fuzziness. Our task is now to find the optimum number of clusters to use and calculate their centres. To obtain this, we made an attempt to modify Fuzzy C means to suit our purpose. We employ the modified algorithm to obtain the cluster centre's coordinates for each spectrum (mineral). The cluster centre will now form a set of predictors (features) that can be used to classify and recognize the mineral in the given spectrum.

3.6.5 Unsupervised Learning Algorithm

The cluster centers are used as input in the unsupervised learning and the algorithm is able to use this as a knowledge base to predict the possible classes of mineral that are present. To be able to achieve this, KSOM was modified. The algorithm is fashioned to have a direct link with the supervised leaning algorithm where it is able to acquire more knowledge to carry out further predictions.

3.6.6 Supervised Learning Algorithm

Various rules which serve as knowledge base for supervised learning were constructed. To be able to carry out this, ANFIS was modified. The network was trained and tested with spectral library of known mineral. The knowledge acquired was shared or transferred to unsupervised leaning algorithm to assist the network in future for future predictions.

3.6.7 Novel Mineral and Volume Estimate

An algorithm was developed to classify mineral that cannot be found in database of the system as novel mineral. Another algorithm was developed to calculate the ratio of the number of pixels in a particular class to the total number of pixels at the given location. This gives an estimate of the amount of mineral in a particular class.

All these algorithms (new or modification of existing ones) were hybridized to form one single algorithm for the developed system. New rules that act as the Knowledge Base for the system also form the major part of the system as explained in the design stage.

3.7 High Level Model

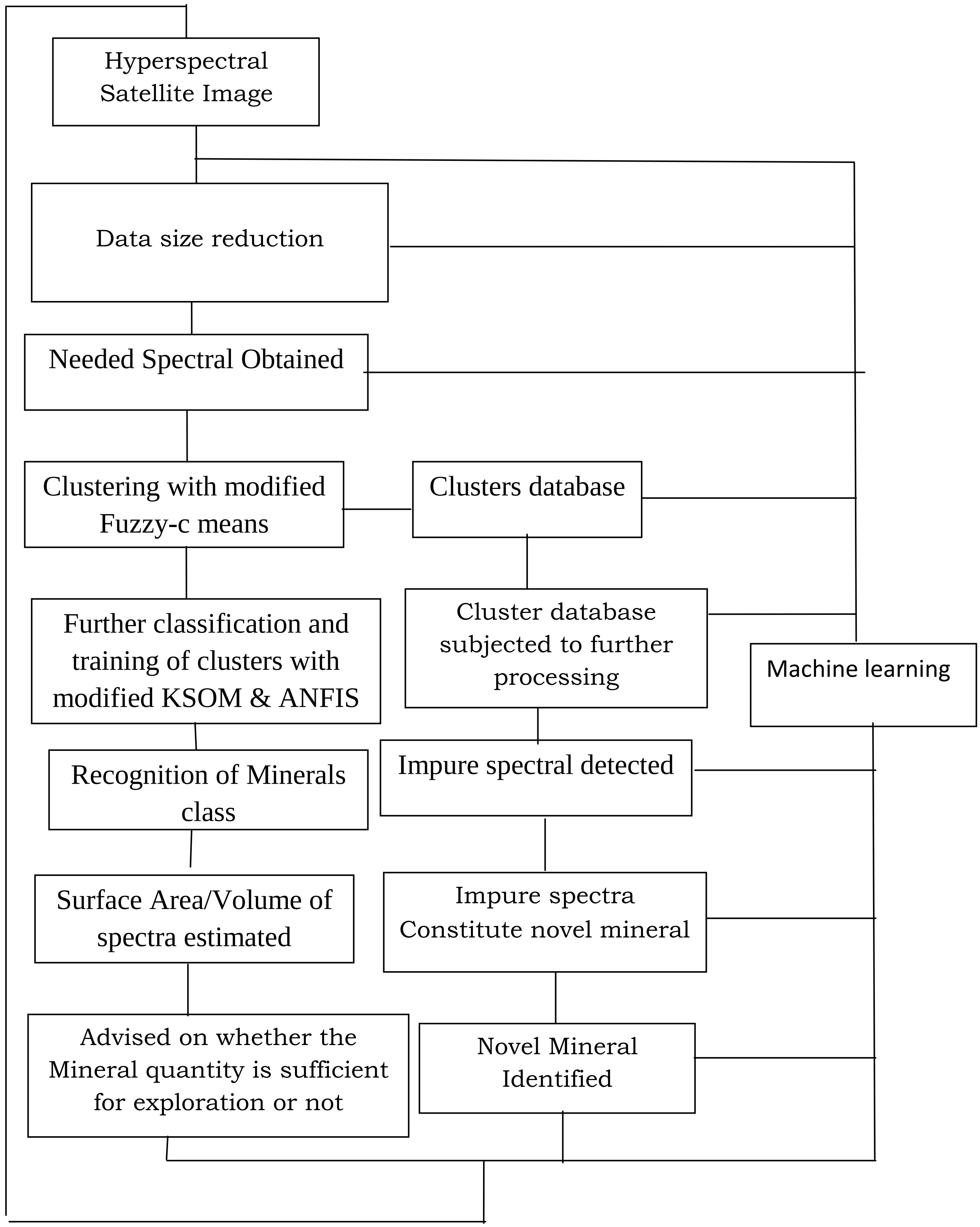


Figure 3.14: High level model of the New System

CHAPTER FOUR

4.0 SYSTEM DESIGN

4.1 INTRODUCTION

In line with our previous discussions, it is clear that the objective of this work is to design an intelligent geoinformatics system that can aid mineral prospecting. The system is to be implemented with series of hyperspectral data to identify classes of minerals that are present. The system should be able to name specific mineral in each class or indicate if it is a novel mineral. The system is also designed in such a way that it can determine the quantity of minerals that are present in each of the classes. All the data are available under Appendix

4.2 OBJECTIVES OF THE DESIGN

The major objective of the system design is that the system should be an intelligent system that should be able to identify classes of mineral that are present in an hyperspectral data, name such minerals and determine the quantity in each class. The design is detailed enough to also identify the noble minerals that are present in such data.

4.3 MAJOR COMPONENTS OF THE SYSTEM

The developed system is divided into various modules. These include: Input, Characterization, Clustering, Unsupervised, Supervised, Novel mineral and reserve volume estimation as shown in figure 4.1.

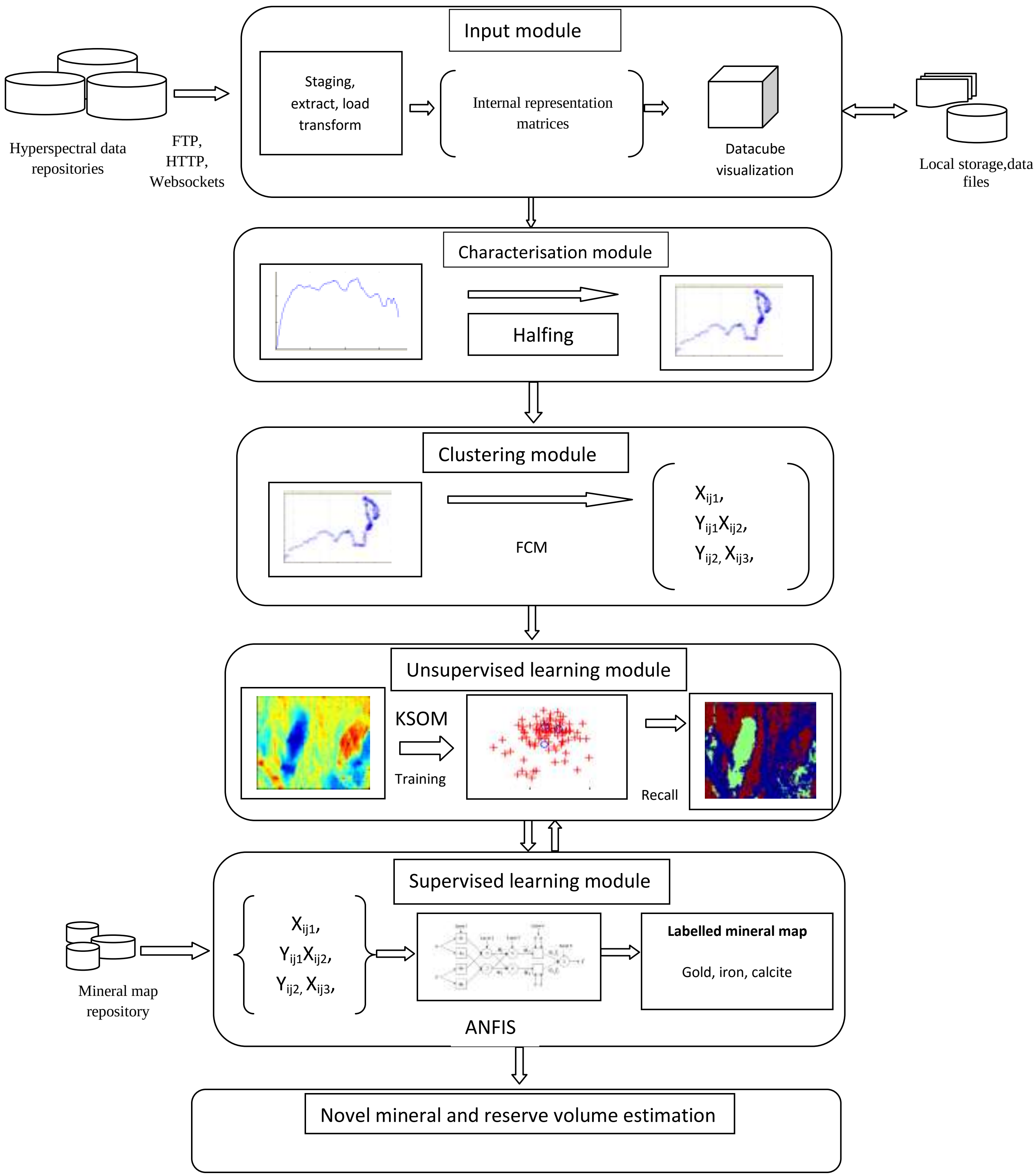


Fig 4.1: General Overview of an Intelligent System for Mineral Prospecting

The detailed explanation of each component is provided in chapter four under analysis of the proposed system.

Having shown the overview of the new system, the next task is to incorporate each of the components into the programming environment in other to produce a programmable geoinformatics intelligent system that can be used for mineral prospecting. This leads to the design of the system menu.

4.3.1 Main Menu

The system consists of main and sub-menus. Mineral Spec is the file name with which the package is being saved. The main menu is then decomposed to obtain different sub-menus. The main menu is shown in figure 4.2 below:

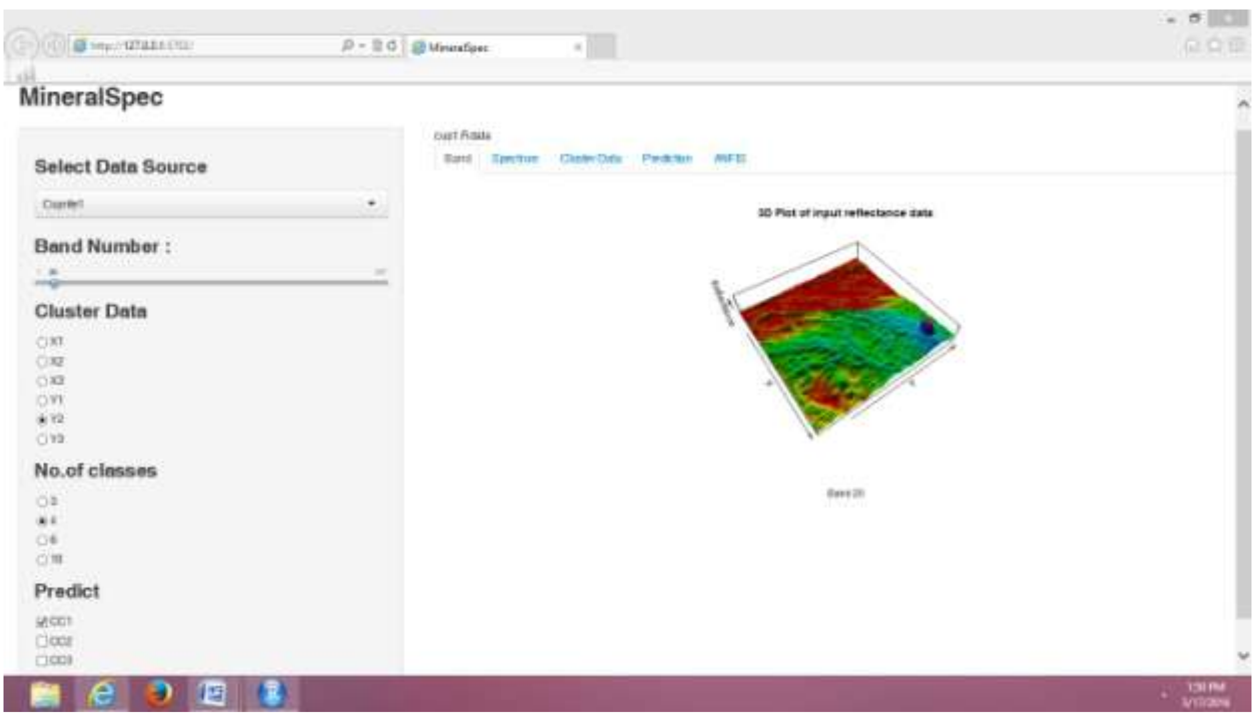


Figure 4.2: The Main Interface Window of the System

Different sub menu that are present in the system are:

(i)Data Source

(ii)Band Number

(iii)Cluster Data

(iv)No of Classes

(v)Prediction

4.3.1.1 Band/Spectrum Sub-menu

Hyperspectral data is made up of band and spectrum of various sizes. The user is expected to choose a particular size at input level when using the new system. It is the menu that controls the input of data. Figure 4.3 below explains further. When we compare this sub menu with figure 4.1, it has a direct link with input module

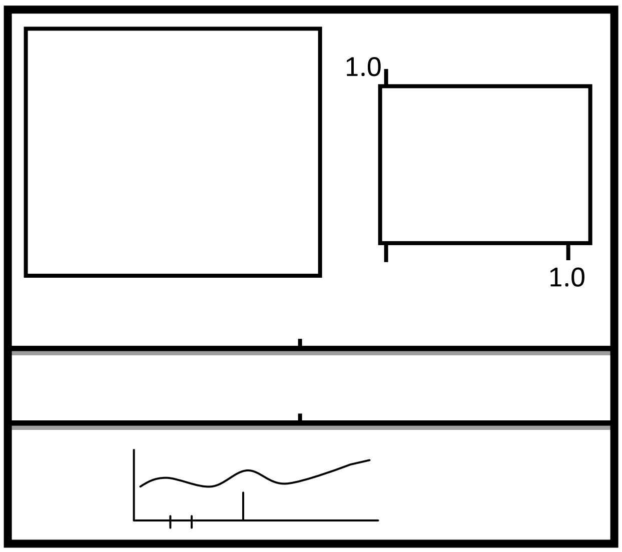


Fig 4.3: The Spectrum Submenu

4.3.1.2 Cluster Data Sub-menu

The new system is able to compute the cluster centres for all the available minerals. The computation will run through 100 by 100 by 357 pixels. The Cluster Data Sub menu handles the computational process and displays the result on the screen inform of images. Figure 4.4 illustrates further. This is obtained from the sub component called characterization and clustering modules in figure 4.1

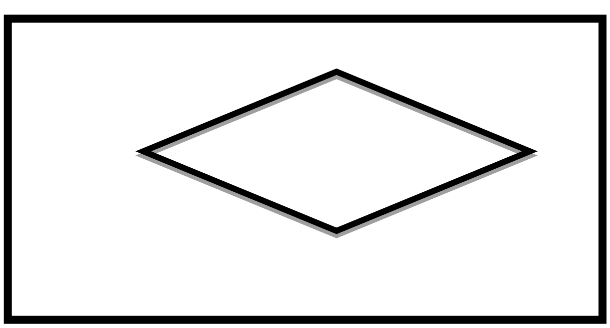


Fig 4.4: The Cluster Data Submenu

4.3.1.3 Modified ANFIS Sub Menu : ANFIS is a typical example of a supervised learning algorithm. For the purpose of this research, it is trained with spectral library of known minerals. This menu interact with KSOM module which is an unsupervised learning algorithm to name the types of minerals in each class as illustrated in figure 4.1

4.3.1.4 Prediction Sub-menu

There are different types of minerals that are present in a given set of data. A particular group is referred to as a class. The new system is able to predict the different types of minerals that are present using Prediction Sub menu. The prediction is based on the calculated cluster centre e.g. cluster centre1(cc1), cluster centre2(cc2), cluster centre3(cc3) as explained earlier under analysis of proposed system in charpter3. See figure 4. 5 for further illustrations.

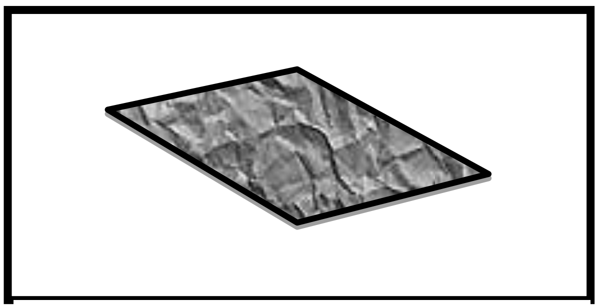


Fig 4.5: The Prediction Submenu

In the new system, the KSOM as an example of unsupervised learning algorithm is linked up with ANFIS as an example of supervised learning algorithm as shown in figure 4.1. The interaction of the two algorithms will be required for any type of prediction to be made by the system .For instance, with this sub menu it is possible for the system to predict the type and quantity of mineral in a particular class. ANFIS has some other sub menus which are :

(i)Data input
(ii)Training data
(iii)Training curve

4.3.1.5 Data Input Submenu

The input variable number indicates the variable name with which the data to be tested or trained is supplied to the new system**.** See figure4.6

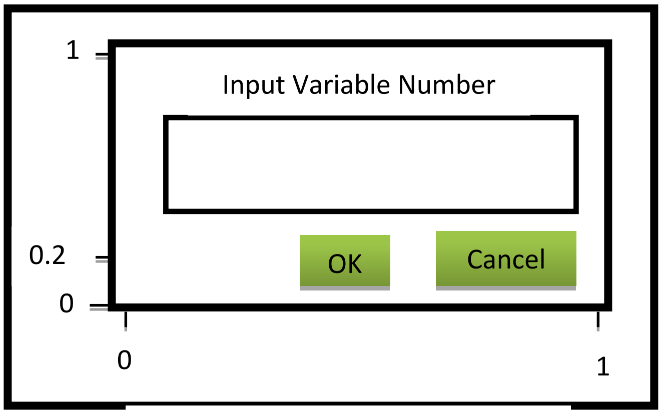


Fig 4.6: Data Input Submenu

4.3.1.6 Training Data Sub-menu

Each of the horizontal line indicates classes of mineral in the given hyperspectral data. See the illustration in figure 4.7.Points that do not fall on a particular line indicate the presence of novel minerals.

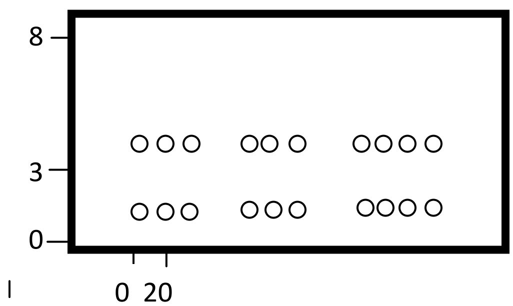


Fig 4.7: Training Data Submenu

4.3.1.7 Training Curve Sub-menu

This shows the learning curve of the supervised learning algorithm where the error continues to approach zero. The closer the error is to zero, the better the training as shown in figure 4.8 below. This is explained further in chapter five (system implementation.

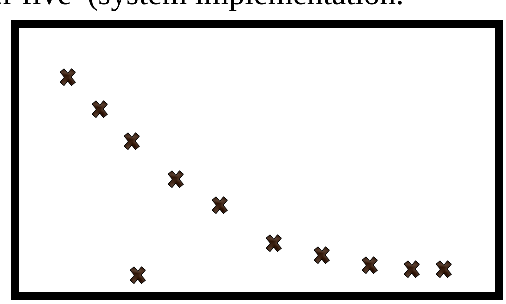


Fig 4.8: Training Curve Submenu

4.4 INPUT / OUTPUT SPECIFICATION

4.4.1 Output Format

In each of the diagram a, b, c and d of figure 4.9, each row (class) stand for a particular group of mineral. The exact name of such mineral is not yet known.

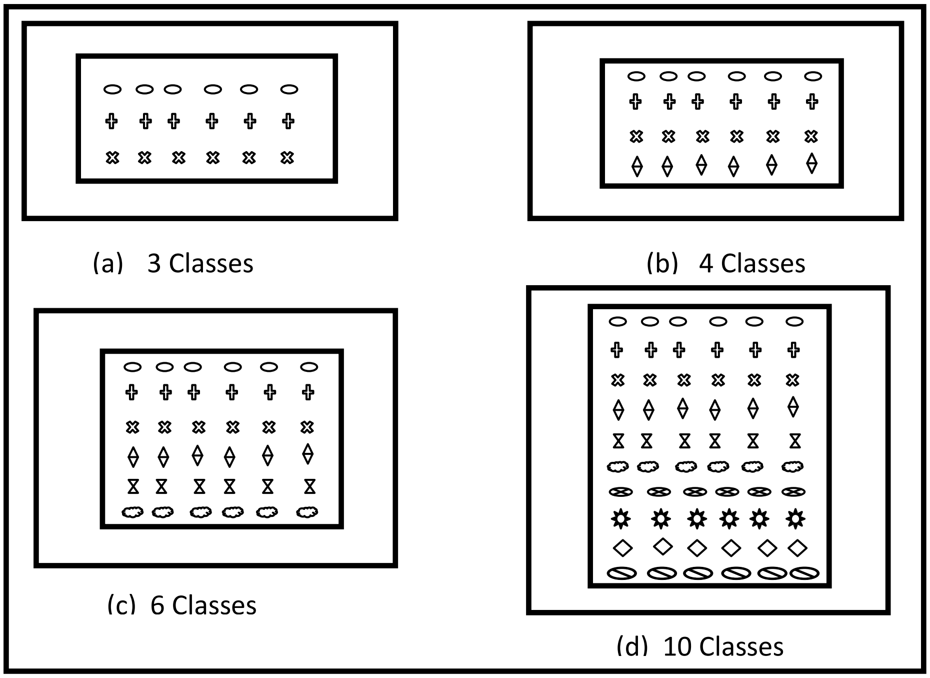


Fig 4.9: Prediction of classes of mineral

4.4.1.1 Identification of Mineral Name

The letters a, b, c… j, in figure 4.10 represent the names of individual minerals .eg. Gold, Aluminum, Iron etc.

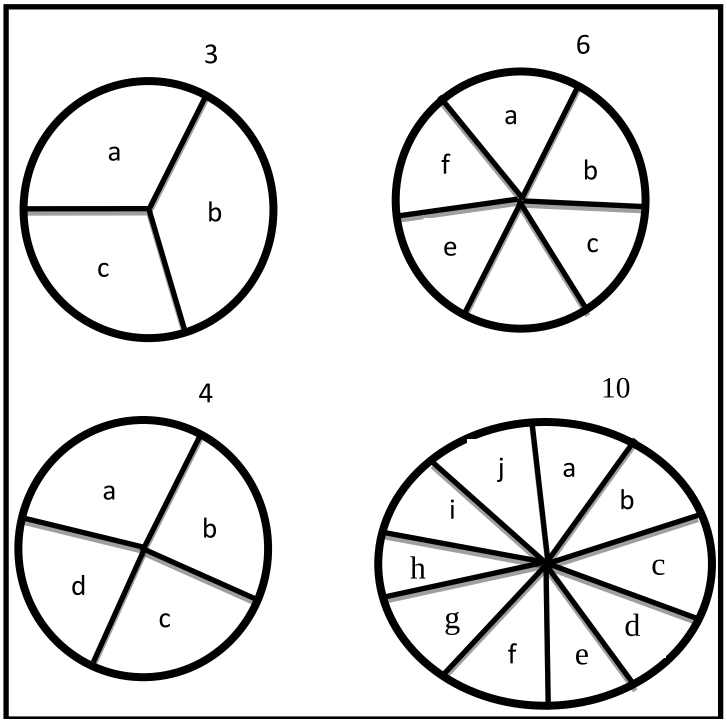


Fig 4.10: Identification of the name of the mineral in each class

4.4.2 Input Format

4.4.2.1 Dimension of Input Data

The hyperspectral data image is of the dimension $Length * Breadth * Band$ where the length is 100; the breadth is 100 and the band is 357. Maintaining a particular length and the breadth, a particular band is chosen at a particular point (Band 50, 75, 100,125 etc.) as an input data. This is shown in table 4.1 below

Table 4.1: Dimension of the Input Data

Length	Breadth	Band
100	100	50
100	100	75
100	100	100
100	100	125
100	100	150
100	100	175
100	100	200
100	100	225
100	100	250

4.4.3 Cluster Centre

4.4.3.1 Cluster Centre Format

Table 4.2: Generated Cluster Centre for Some Selected Bands

Band	Cluster Centre
50	x_1
100	x_2
150	x_3
200	y_1
250	y_2
300	y_3

It is possible to determine the cluster centre at various points x_1,x_2,,x_3 and so on for each of the bands selected. Table 4.2 explain further.

4.4.3.2 Mineral Class

Table 4.3: Prediction of Mineral Classes using Different Cluster Centre

L	B	Bands	No. of Classes
100	100	50	$C1$
100	100	100	$C2$
100	100	150	$C3$
100	100	200	$C1, C2$
100	100	250	$C1, C3$
100	100	300	$C2, C3$
100	100	350	$C1, C3$
100	100	400	$C2, C1$
100	100	450	$C1, C2, C3$

Table 4.3: Prediction of Mineral Classes

4.4.4 Output Specification

Table 4.4: Output format of visualization images

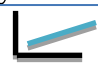
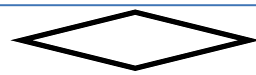
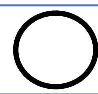
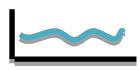
Symbol name	Visualization	Symbols
Spectrum	Line Graph	
Characterization Map	Dot Plot	• • • • •
Band	3-D Surface	
Abundant	Pie-Chart	
Learning Curve	Line Graph	
Class Count	Count Plot	

Table 4.4 shows the output format of visualization images

4.5 HYBRIDIZED ALGORITHM OF THE NEW SYSTEM

Input data
##Split into train and testing data
Datatrain <= $dtr\ [m_i, n_j, f]$
Datatest <= $dts\ [m_i, n_j, f]$

Select frequency band
freqband <= $dt\ [f_1 \dots f_n]$

Using x_n, y_n as the coordinate of the band
$f_n = f(x_n, y_n)$

Visualization of hyperspectral data
Cube <= $[M, N, F]$

Band slice of the hyperspectral data
$Slice$ <= $[m_i, n_j, f_n]$
$[S_{i,j,n}]$ <= Slice
$Display\ [S_{i,j,n}]$
Spectrum <= $[m_i, n_j]$

Plot of spectrum for each mineral
$[V_s]$ <= plot (Spectrum)
Display $[V_s]$

(2)
Obtain the Spectrum data
$[A_n]$ <= Spectrum
$getMatrix[A] <= [a_{r,c}]$
r<= row number, and c<= column number

#Data Normalization
Find the maximum element of the matrix
$a_{i,j}$ <= max(matrix$[A]$)
i^{th}andj^{th}column

Divide all elements matrix [A] by the maximum element
$$\text{matrix}[B] = \frac{\text{matrix}[A]}{a_{i,j}}$$
displaymatrix$[B]$
$[b_{r,c}]$ <= matrix$[B]$

Assign each element of [B] to its respective coordinates
Matrix$[b_{r,c}]$ <= $[(x_i, y_j)_{r,c}]$
wherei, j is the coordinate of each data points in the r^{th} row, c^{th}column
$[x_i, y_j] \equiv [(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)]$
plot(x_i, y_j) : $1 < i \leq n$
$$x_c = \frac{x_1 + x_n}{2}$$
list[1] = $[x_1, x_2, \dots, x_c]$
list[2] = $[x_c, x_{c+1}, \dots, x_n]$
Charx $[List] = (list[1], list[2])$
plot (Charx$[List]$)

(3)
$[D] <= Charx[List]$
##Input data set D
$D = Matrix[x_i]_1^n$
##Initialization: Define number of clusters n_c where $1 \leq n_c \leq n$
##Let the weight of the exponent be m and the termination toleration be t then define a particular U
Let U <= matrix$[\mu]_i^j$
Repeat
for $t = 1, 2, \dots, n$

Step 1:
##Compute the Cluster Centre
[define$[C_i{}^t]$ ... $epoch = t$
$V =$ matrix$[\mu]_i^j$

$P = (V^{t-1})^m$
$G = [(P * \text{matrix}[\, X_j])] \,/\, \text{matrix}\,[P]$

Step 2:
Calculate the distance: Compute the Euclidean distance ${D^2}_{ijA}$ as
matrix[$X_j]_1^n$, matrix[$C_i]_1^n$
${D^2}_{ijA} <= Transpose[\text{matrix}[X_j] - \text{matrix}[C_j]]$
Update fuzzy partition matrix

$$V = \frac{1}{[(SQRT\ (D_{ijA}) ** 2) ** 2]}$$

End for
Until
$[SQRT(D_{ijA})]_1 - [SQRT(D_{ijA})]_2 < \varepsilon$

Clustering Algorithm
Consider the cluster point $X_j$from a chosen cluster centre c_i
Compute the Euclidean distance, D_{ijA}between the points $X_j$and c_i
${D^2}_{ij} \leq \text{mod}[X_j - c_i] ** 2$
$\text{mod}[X_j - c_i] ** 2 <= \text{Transp}\ [X_j - c_i] * Adj[X_j - c_i]$
${D^2}_{ij} <= \text{Transp}\ [X_j - c_i] * Adj[X_j - c_i]$
$\text{Mod}[{{D^2}_{ij}}^{(t)} - {{D^2}_{ij}}^{(t-1)} < \varepsilon$
End

SOM Algorithm
Step 1:
##Input the input Neuron mat MAT[X], MAT[Y].
Out Sum of Neurons =MAT[X]*MAT[Y]
S= 0 to S-1 is the number of neurons in the layer
Step 2:
To set up competitive layer matrix
Competitive layer is at the output layer
Output neuron matrix: MATO[X], MATO[Y]
For simplicity, we want to have a square matrix
MATO[X] = MATO[Y]
Sum of competitive neuron S_o=MATO[X]*MATO[Y]
Where S_o=0 to S_o-1
Step 3:
##Initialize connection weight between input layer neuron and competitive layer neuron W_{ij}
$d_0 <= NP$ where NP is the neighbourhood parameter

$d_0 <= out\frac{Mat[x]}{2}$

Step 4:
##Compute the winning neuron j_c which is the minimum Euclidean distance from the input layer to competitive layer
$Mod[E[J]] \leq SQRT\left[Sum[(W_{ij} - x_i) ** 2]\right]$
J=0 to J-1
Compare $Mod[E(0)] to\ Mod[E(j)]$
If $Mod[E(j_c)]$is the minimum THEN $Mod[E(j_c) <= Min(Mod[E(J)]$
Compute Euclidean distance for each competitive layer neuron
$mod\ [E(j_1) \leq [SQRT(W_{11} - x_1) ** 2 + (W_{21} - x_2) ** 2 + \cdots + (W_{ij} - x_i) ** 2$
Step 5
Update weight for each connection for all neurons $j$and for all i
$W_{ij}[New] <= \ W_{ij}[Old] + \Delta W_{ij}[New]$
$\Delta W_{ij} <= W_{ij}[New] - W_{ij}[Old]$
Step 6:
Update learning rate, $\propto t$
$\propto t <=\propto_0 * [1 - \frac{t}{T}]$
Step 7:
Reduce radius of neighbourhood for d_t times
$d_t <= INT[d_0 * \propto_t]$
Step 8
Increase iteration
$t \leq [t + 1]$
$if\ t < T$
Repeat step 5 to 8
Step 9:
Repeat with next pattern D_0steps 4 to 9

For $t = 0, 1, 2, \ldots\ldots\quad do$
##Initialize weight
##Measure the Euclidean Distance of each competitive layer neuron with respect to the given input Neuron with minimum distance
##Initialize weight
$[W] <=$ Random Weight
$[X] \leq$ Input weight of each competitive layer
##Let the Euclidean distance, weight and layer neuron with respect to the input weight be ed
$*ed = [W] - [X]$

$ed \leq Min\big[[W] - [X]\big]$
If $ed < \ \varepsilon$
Update weight
Goto *
Back Propagation
$ec <= do - co$
##whereec is the error calculated,
$do$is the desired output and
$co$is the calculated
Process of updating weight for clusters
##Initialize the epoch
$t = 0$
##Set the weight vector
$[W_{ij}] <= [WV]$whereWV is the weight vector and
$[X] \leq [\text{Input Vector}]$
$e <= [X] - [W]$
##Select the wining neuron
Update the winning neuron
$if\ [X]$is not selected goto step 0
$if\ e > \varepsilon$,(##Stepping condition)
$t = t + 1$
End

4.6 Input Rules of the System

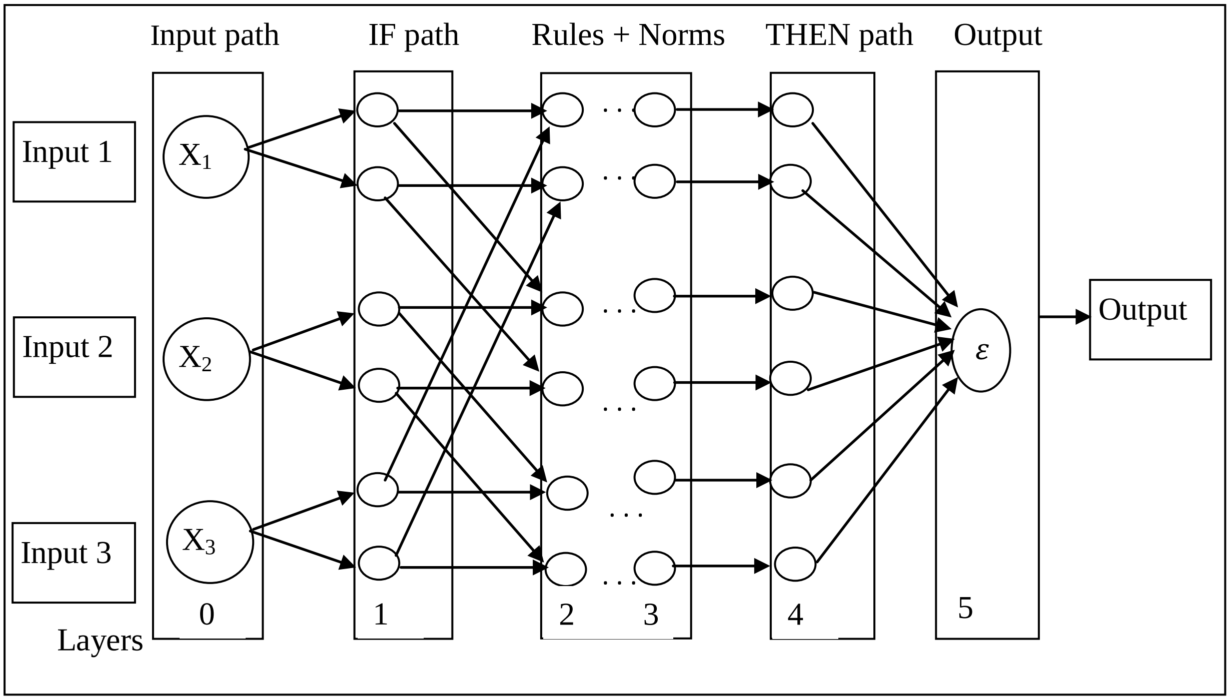


Figure 4.11: ANFIS Structure of the Developed System

From figure 4.11, five network layers are used to perform the following fuzzy inference steps:

Layer 0: This controls the membership function which is the cluster centre. Three cluster centres X_1, X_2, X_3 serve as the input to the system.

Layer 1: This is for input fuzification which fuzzifies the input data.

Layer 2: This is the Fuzzy Set Database Construction which manages the database for the system.

Layer 3: This is the Fuzzy Rule-base Construction which manages the various rules used by the system. It follows therefore that the layer 2 and 3 serve as the Inference Engine that controls both the database and the rule base of the system.

Layer 4: This is the decision making layer that is concerned with making useful decision based on the output generated from layer 2 and 3 (Inference Engine of the system).

Layer 5: This is the final layer. It gives the final output of the system after defuzzification process.

Various rules are constructed as shown below to take care of the database and the knowledge base as well as the decision of the system. Apart from the rule construction, they were also expressed diagrammatically as shown in figure 4.12, 4.13 and 4.14. The resultant rules generated at the output stage after defuzzification is also expressed diagrammatically in figure 15 using centre of gravity approach. The diagram was simplified as much as possible.

Rule 1: $\boldsymbol{IF}\ CC1\ is\ medium$
$\boldsymbol{AND}\ CC2\ is\ low$
$\boldsymbol{AND}\ CC3\ is\ medium$
$\boldsymbol{THEN}\ CC4\ is\ medium$

Rule 2: $\boldsymbol{IF}\ CC1\ is\ medium$
$\boldsymbol{AND}\ CC2\ is\ medium$
$\boldsymbol{AND}\ CC3\ is\ medium$
$\boldsymbol{THEN}\ cc4\ is\ medium$

Rule 3: $\boldsymbol{IF}\ CC1\ is\ low$
$\boldsymbol{AND}\ CC2\ is\ medium$
$\boldsymbol{AND}\ CC3\ is\ medium$
$\boldsymbol{THEN}\ CC4\ is\ medium$

Rule 4: $\boldsymbol{IF}\ CC1\ is\ low$
$\boldsymbol{AND}\ CC2\ is\ low$
$\boldsymbol{AND}\ CC3\ is\ medium$
$\boldsymbol{THEN}\ CC4\ is\ low$

Rule 5: $\boldsymbol{IF}\ CC1\ is\ low$
$\boldsymbol{AND}\ CC2\ is\ low$
$\boldsymbol{AND}\ CC3\ is\ low$
$\boldsymbol{THEN}\ CC4\ is\ low$

Rule 6: $\boldsymbol{IF}\ CC1\ is\ medium$
$\boldsymbol{AND}\ CC2\ is\ low$
$\boldsymbol{AND}\ CC3\ is\ low$
$\boldsymbol{THEN}\ CC4\ is\ low$

Rule 7: $\boldsymbol{IF}\ CC1\ is\ medium$
$\boldsymbol{AND}\ CC2\ is\ medium$
$\boldsymbol{AND}\ CC3\ is\ low$
$\boldsymbol{THEN}\ CC4\ is\ medium$

Rule 8: $\boldsymbol{IF}\ CC1\ is\ low$
$\boldsymbol{AND}\ CC2\ is\ medium$
$\boldsymbol{AND}\ CC3\ is\ low$
$\boldsymbol{THEN}\ CC4\ is\ low$

Rule 9: $\boldsymbol{IF}\ CC1\ is\ medium$

$\boldsymbol{AND}$ $CC2$ $is\ high$
$\boldsymbol{AND}$ $CC3$ $is\ medium$
$\boldsymbol{THEN}$ $CC4$ $is\ medium$

Rule 10: $\boldsymbol{IF}$ $CC1$ $is\ medium$
$\boldsymbol{AND}$ $CC2$ $is\ high$
$\boldsymbol{AND}$ $CC3$ $is\ high$
$\boldsymbol{THEN}$ $CC4$ $is\ high$

Rule 11: $\boldsymbol{IF}$ $CC1$ $is\ medium$
$\boldsymbol{AND}$ $CC2$ $is\ medium$
$\boldsymbol{AND}$ $CC3$ $is\ high$
$\boldsymbol{THEN}$ $CC4$ $is\ medium$

Rule 12: $\boldsymbol{IF}$ $CC1$ $is\ high$
$\boldsymbol{AND}$ $CC2$ $is\ high$
$\boldsymbol{AND}$ $CC3$ $is\ medium$
$\boldsymbol{THEN}$ $CC4$ $is\ high$

Rule 13: $\boldsymbol{IF}$ $CC1$ $is\ high$
$\boldsymbol{AND}$ $CC2$ $is\ high$
$\boldsymbol{AND}$ $CC3$ $is\ high$
$\boldsymbol{THEN}$ $CC4$ $is\ high$

Rule 14: $\boldsymbol{IF}$ $CC1$ $is\ high$
$\boldsymbol{AND}$ $CC2$ $is\ medium$
$\boldsymbol{AND}$ $CC3$ $is\ medium$
$\boldsymbol{THEN}$ $CC4$ $is\ medium$

Rule 15: $\boldsymbol{IF}$ $CC1$ $is\ high$
$\boldsymbol{AND}$ $CC2$ $is\ low$
$\boldsymbol{AND}$ $CC3$ $is\ low$
$\boldsymbol{THEN}$ $CC4$ $is\ low$

Rule 16: $\boldsymbol{IF}$ $CC1$ $is\ high$
$\boldsymbol{AND}$ $CC2$ $is\ high$
$\boldsymbol{AND}$ $CC3$ $is\ low$
$\boldsymbol{THEN}$ $CC4$ $is\ high$

Rule 17: $\boldsymbol{IF}$ $CC1$ $is\ high$
$\boldsymbol{AND}$ $CC2$ $is\ low$
$\boldsymbol{AND}$ $CC3$ $is\ high$
$\boldsymbol{THEN}$ $CC4$ $is\ high$

Rule 18: $\boldsymbol{IF}$ $CC1$ $is\ low$
$\boldsymbol{AND}$ $CC2$ $is\ low$
$\boldsymbol{AND}$ $CC3$ $is\ high$
$\boldsymbol{THEN}$ $CC4$ $is\ low$

Rule 19: $\boldsymbol{IF}$ $CC1$ $is\ low$
$\boldsymbol{AND}$ $CC2$ $is\ high$

$\boldsymbol{AND}\ CC3\ is\ low$
$\boldsymbol{THEN}\ CC4\ is\ low$

Rule 20: $\boldsymbol{IF}\ CC1\ is\ low$
$\boldsymbol{AND}\ CC2\ is\ high$
$\boldsymbol{AND}\ CC3\ is\ high$
$\boldsymbol{THEN}\ CC4\ is\ high$

4.7 MEMBERSHIP FUNCTION OF THE FUZZY RULE

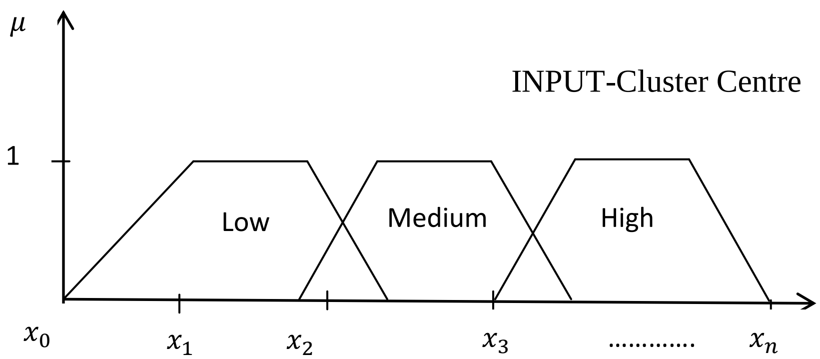


Fig 4.12: Membership Function of the Input

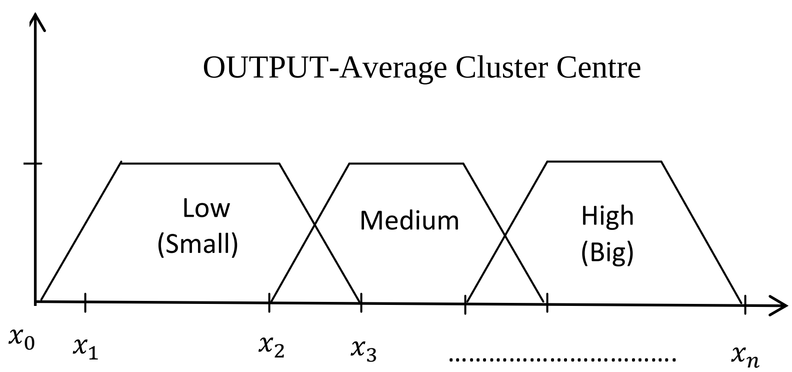


Fig 4.13: Membership Function of the Output

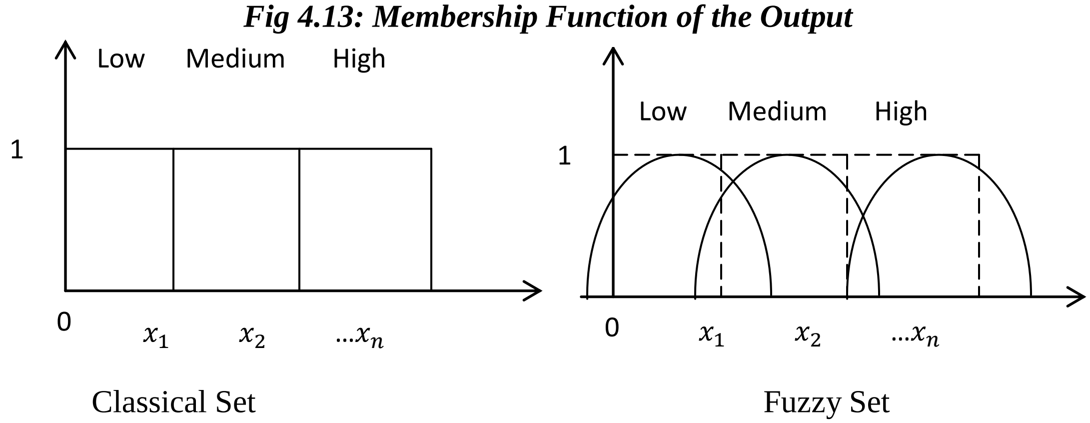


Figure 4.14: Membership Function of a classical set and Fuzzy set

In a classical set, a member of the set strictly belongs to a particular class of the set. But in fuzzy set, a member can partly belong to a particular set and this explains why a fuzzy set has a varying degree of membership.

Assuming we have a fuzzy set A with an element x being a member **THEN**

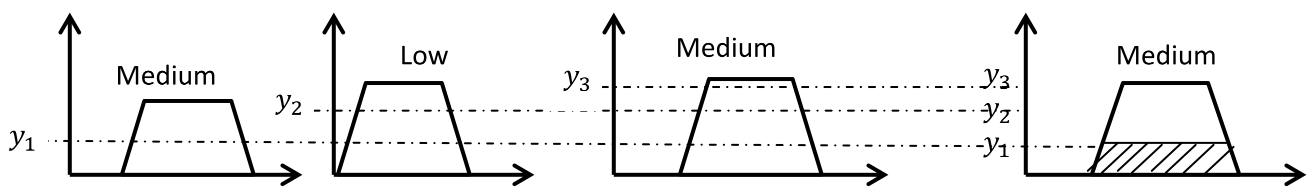
$$C = (x, \mu_A(x) \forall x \in X)$$

Where x has a membership function$\mu_A(x)$. The degree of membership varies between 0 **AND** 1 i.e.

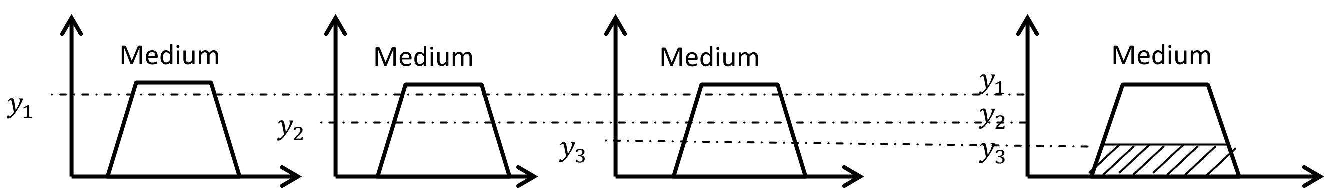
$$\mu_A(x) \in [0 \ldots 1]$$

$C = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \cdots + \frac{\mu_A(x_i)}{x_i} = \sum \frac{\mu_A(x_i)}{x_i}$

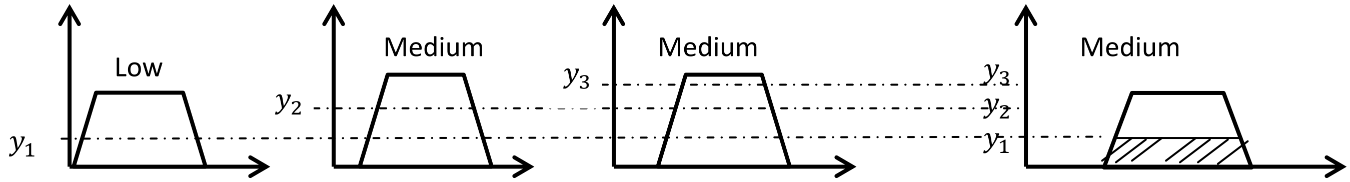
Rule 1



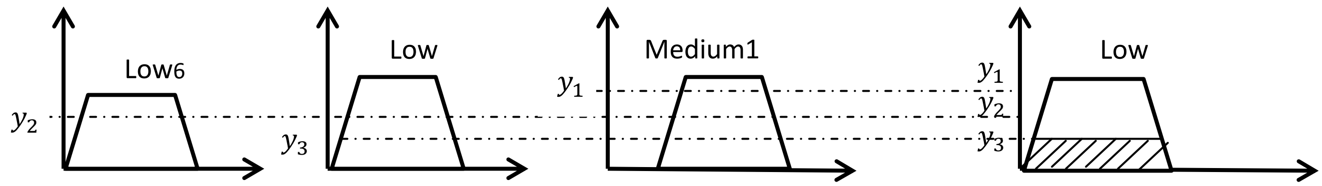
Rule 2



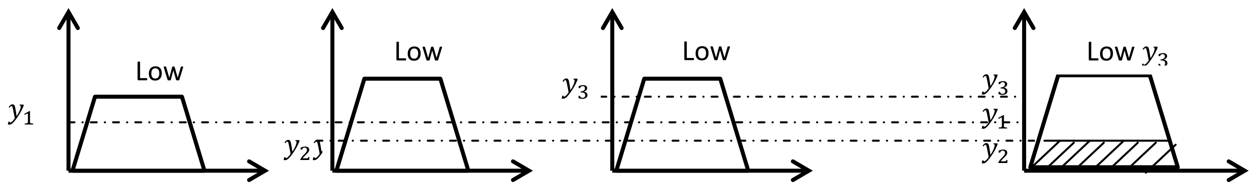
Rule 3



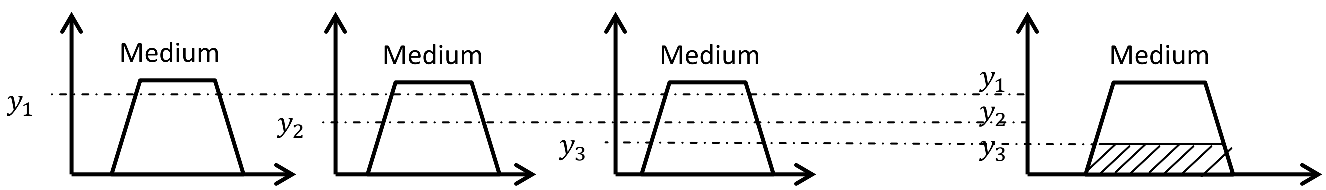
Rule 4



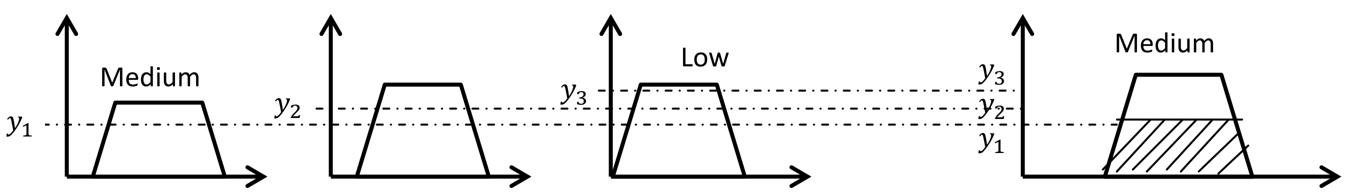
Rule 5



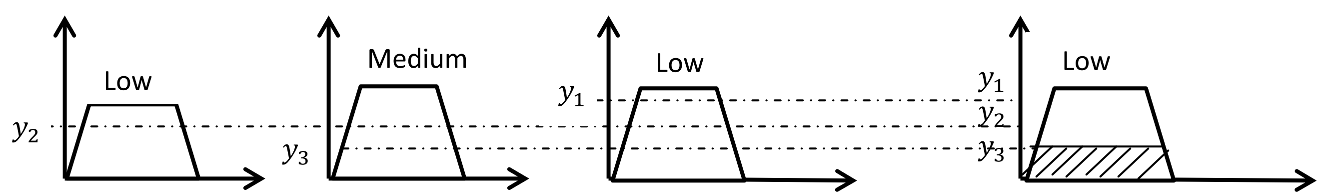
Rule 2



Rule 7



Rule 8



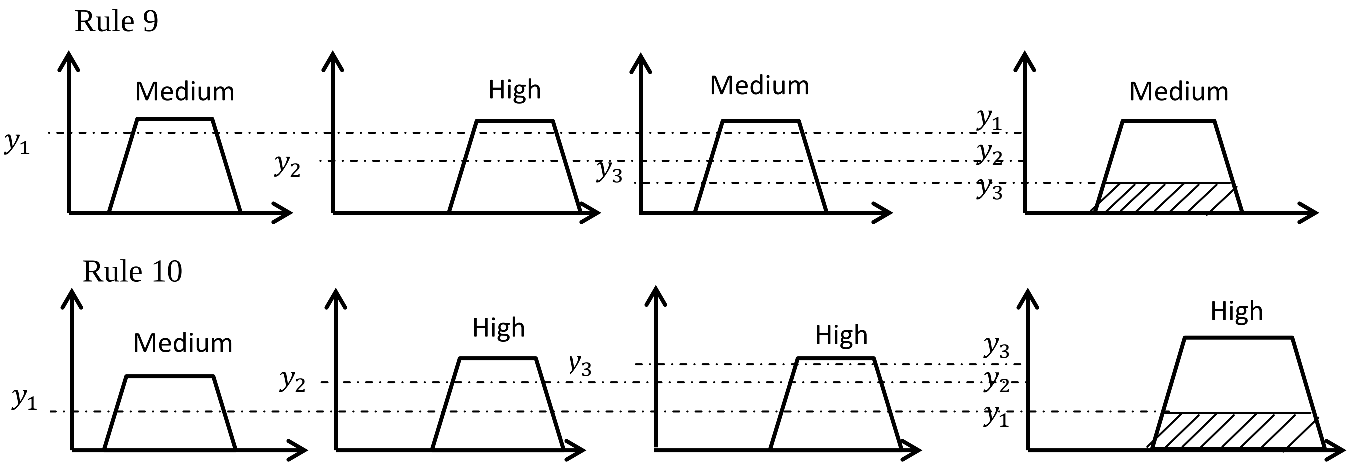


Fig 4.15: Illustration of Fuzzy Output Rules

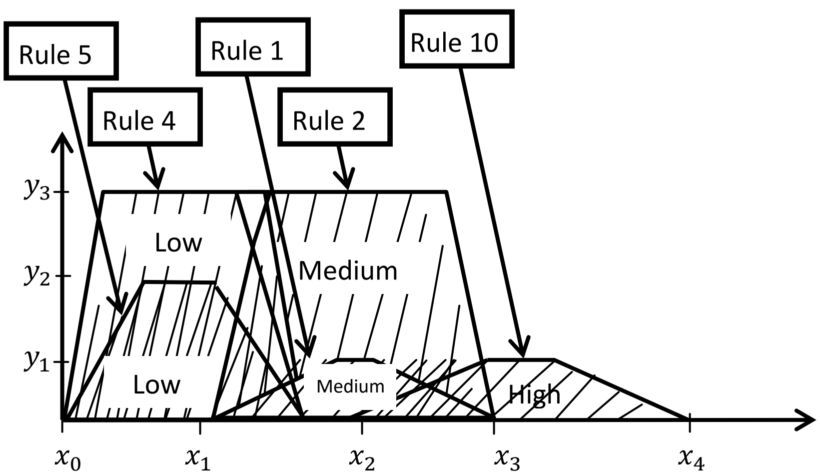


Fig 4.16: Fuzzy Output Determination using Centre of Gravity

CHAPTER FIVE

5.0 SYSTEM IMPLEMENTATION

5.1 INTRODUCTION

Hyperspectral data consist of arrays of matrices that require intensive array and matrix calculations. Moreover, the use of computational based artificial intelligence methods also involves high volume array and matrix calculation. Thus, it is necessary to select computing environment that has capabilities for array and matrix calculations and visualization.

In the following, a prototype implementation of the system in R Language using R Studio environment is presented. The main focus in the implementation is to present a working prototype that proves the correctness of the developed methodology of developing an intelligent geoinformatics system for solid mineral prospecting.

Generally the modules are implemented as RScript programs with the use of Tcl/Tk to design the front end for data presentation and visualization. The Tcl/Tk provides a window that made RScript compatible with other operating system e.g. UNIX, Linux e.t.c.

5.2 HARDWARE AND SOFTWARE REQUIREMENTS

1. Hardware Requirements

Dual core processor with 2 GB memory

At least, 100 GB hard disk

With high speed internet connection

2. Software requirement

32/64 bits Linux or Windows operating system

R Studio and MATLAB

5.3 PROGRAMMING LANGUAGE USED

R programming Language

R programming language is known for image processing and visualization and widely applied in solving real life problems where large amounts of data are involved. Hyperspectral data are always very large because of its high dimensionality and therefore require programming language that is able to process large data. R programming language is also known for its high degree of flexibility. This enhances proper documentation and maintenance.

It is also an Open access programming language which attracts the interest of researchers all over the world. To be able to design and implement a good intelligent system, ANFIS structure of MATLAB was incorporated into R studio.

5.4 Program Development

(i) The input Module

The input module uses a model view control architecture to read in data in the form of hyperspectral data format. A Graphic User Interface with ability to search directories for data files was constructed using Tcl/Tk. The user selects the appropriate data file using point and click views. The selected file is then read with appropriate reading functions, with the possibility of selecting the rows, columns and bands to be read from the data. The data is loaded into a matrix data structure from which particular rows, columns or bands can be read for further processing. In addition, this matrix data structure enables the visualization of data cube, band slices, or spectrum of individual mineral.

(ii) Characterization module

The spectral data for particular mineral (x_i, y_i) is read into an array zk $(k = 1 \ldots n\ bands)$. In order to generate a characterization map for the mineral, the first half of the spectral data is plotted as x-coordinates against the other half as y-coordinates. The generated map uniquely characterizes the mineral and the map will be the same for similar mineral. Furthermore, mineral that are quazi-similar (alike with little variations) will generate maps that are nearly the same. A plot of the data and the generated characterization map is provided to aid visualization.

(iii) Clustering module

The clustering module is implemented using modified fuzzy c-means clustering algorithm. The characterization data for each mineral is clustered to obtain cluster centre data. Stability problems limit the number of cluster that can be used to three. This is adequate enough as this gives us six features (coordinate pairs for each of the three clusters) with which a particular mineral is clustered for further classification. Moreover, the cluster centres of similar mineral will be close to one another, and this is the reason why one will chose clustering as a method for extracting features that can be used to classify the mineral. The cluster centre data for each mineral is then collected into a matrix data structure that forms the basis for visualization, further processing and storage. This forms intermediate data file that can be used to run subsequent modules.

(iv) Unsupervised Learning Module

This module can be run subsequently after the previous module using the cluster centre data that is already in memory or with the stored cluster centre data file. A sample of cluster centre data for mineral is selected and fed as input into the network. The network learns to classify the mineral into classes depending on the given number of output neurons. It is practical to have as many output neurons as the number of classes in the data. The network learns to differentiate classes that are truly different. The trained network is used to classify the cluster centre data for each of the classes to obtain classification predictor map. A colormap of the classification shows the distribution of minerals in the area.

(v)Supervised Learning Module

The training data file contains samples for chosen mineral with the cluster centre data for such mineral as input (six inputs) and the numerical value of the class of such mineral as output. The supervised learning module works with two sets of data. These include the training data set and the testing data set. The network is trained with spectral library of known minerals. The training of the network is by selection of appropriate setting parameter which is required to achieve adequate learning. The effectiveness of the training is verified and confirmed through various test using the testing data set. The effectiveness is detailed in the test and result section (chapter 6). Having learned adequately enough, the network is able to recognize the names of the mineral in the testing data. Peradventure there is a mineral in the testing data that does not belong to any of the classes of the training dataset, such mineral will be referred to as noble mineral and of course the mineral will not fall on the same line as that of the testing data but on a new line. Additional sample of such noble mineral will be used to train the network further to verify its stability so as enable the network to recognize it in the future.

The network will then link up with that of unsupervised learning and share the knowledge with it. The SOM quickly uses the knowledge to name those mineral classes that have been identified initially. The trained network is only able to recognize mineral for which it was trained. At the output, such mineral will fall on a particular line for that class. If a sample for a class for which the network has not been trained is presented, its output will fall on a new line. Such sample will be called novel mineral as earlier discussed

(vi) Mineral reserve (abundance) estimation

The abundance estimation module generates the quantity or volume of mineral in each of the classes. Hence, this determined the quantity or volume of mineral in a particular class. To arrive at this solution, the system computes the ratio of the number of pixels in a particular class to the total number of pixels in a particular location. The quantity of mineral count in each class gives the approximate quantity or volume in that class. Thus, a mineral class that has a pixel's count of 2500 in a location of 10000 pixels area has an abundance of a quarter of the study area.

5.5 Program Testing

Data

The test data consists of spectra data for Cuprite, Nevada. The data consists of 100 by 100 pixels with 357 band spectrum ranging from 0.4 μm to 2.5 μm. The interface of the system is shown in figure 5.1 while Figure 5.2 shows the data cube visualization while Figure 5.3 shows a colormap slice (a band) of the given data. Figure 5.4 shows the band data map.

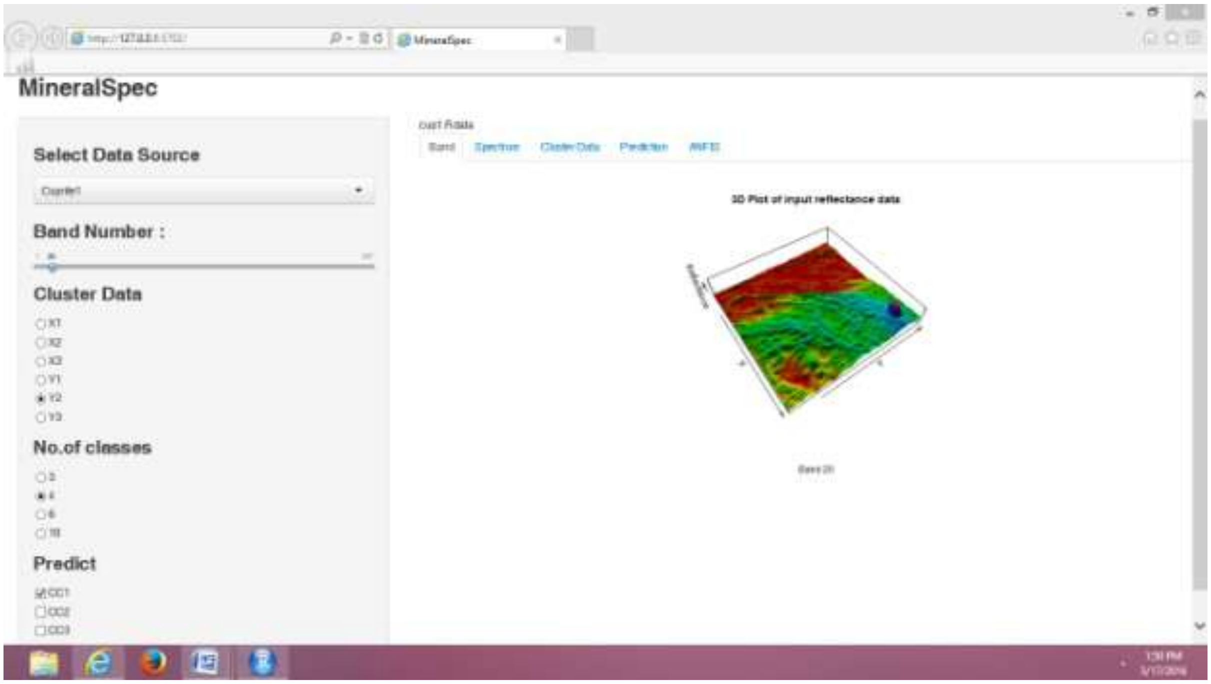


Figure 5.1: The Main Interface Window of the System

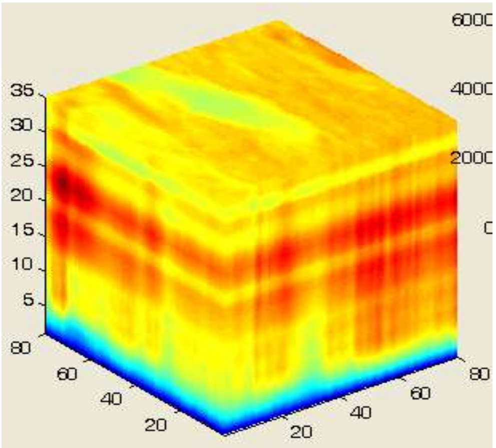


Figure 5.2: Data Cube Image of Hyperspectral Data

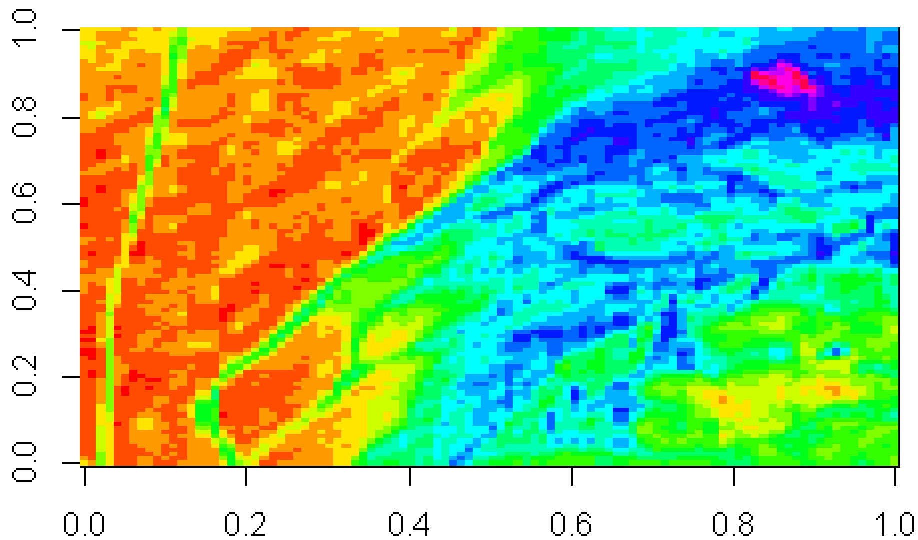


Figure 5.3: A Band (Slice) of Hyperspectral Data

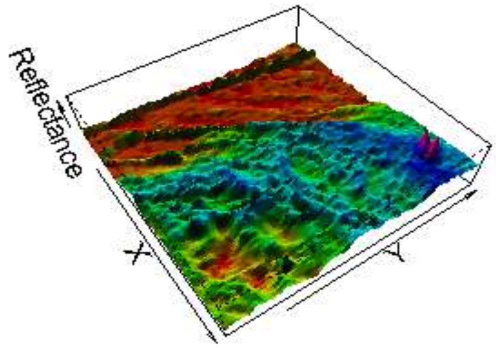
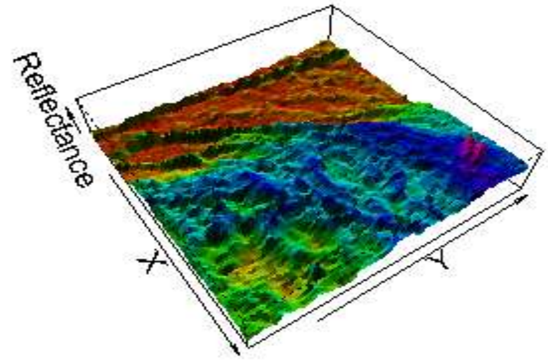
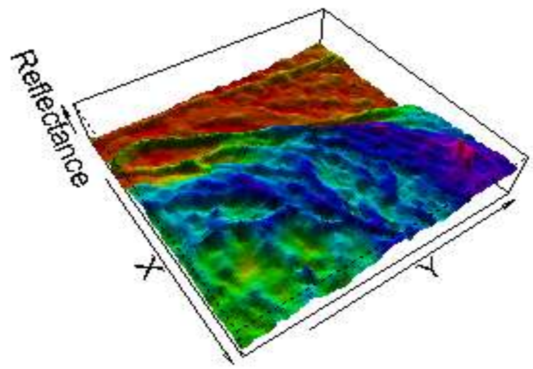
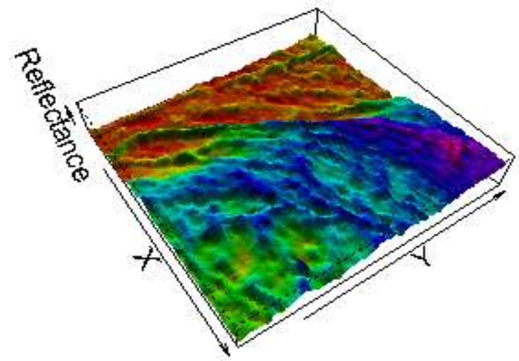
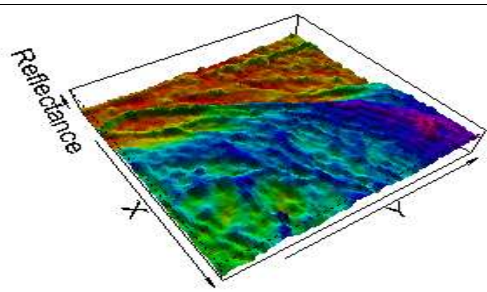
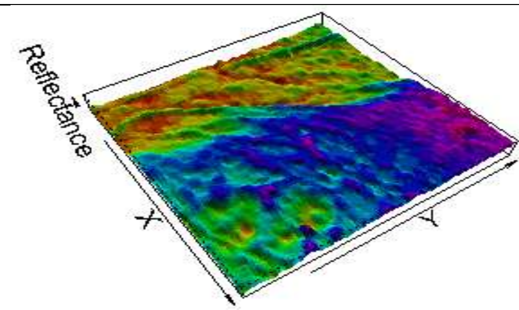
	3D Plot of input reflectance data	
	Band 50	Band 100
		
	Band 150	Band 200
		
	Band 250	Band 300
		

Fig 5.4: 3D Plot of Some Bands of the Input Data

Processing of Spectrum for Mineral

The spectrum for each mineral is selected in turn, displayed in figure 5.5 and turned into characterization map as explained under system design. The characterization map for a particular mineral is shown in figure 5.6. The characterization map is then clustered to obtain 3 cluster centers marked in red in figure 5.6. The cluster centre data for each mineral is then calculated in turn and stored in a cluster centre data structure for file storage or further processing. The cluster centre data distill the essential features for classification and recognition of mineral classes in the given data. The cluster centre image is displayed in figure 5.7. The result is expressed in three different columns. The first column is for cluster centre 1, the second column is for cluster centre2, and the last column is for cluster centre3. Each of the cluster centres is made up of both x and y coordinates point. Obviously, this generated 6 images.

The system then can be used to generate mineral prediction map as shown in figure 5.8. The mineral prediction map shows the distribution of minerals at the given location. The maps were obtained at different cluster centres. At cc1, we can obtain mineral at three classes: 3, 4 and 6. This is displayed in the first row of the diagram. Similarly, at cluster centre2, we can obtain mineral distribution at classes 3, 4 and 6. This is displayed in the second row. For cluster centre3, the mineral distribution is displayed in row3. Combining all the 3 clusters i.e. cluster center 1, 2 and 3, the mineral distribution at the three classes 3, 4 and 6 is displayed in row4. The prediction is done by unsupervised learning algorithm with the help of supervised learning algorithm.

The program is run for different numbers of output neurons and epochs as shown in the results obtained. Figure 5.9 and 5.10 show the plot of learning and class count plot of the training respectively for the system.

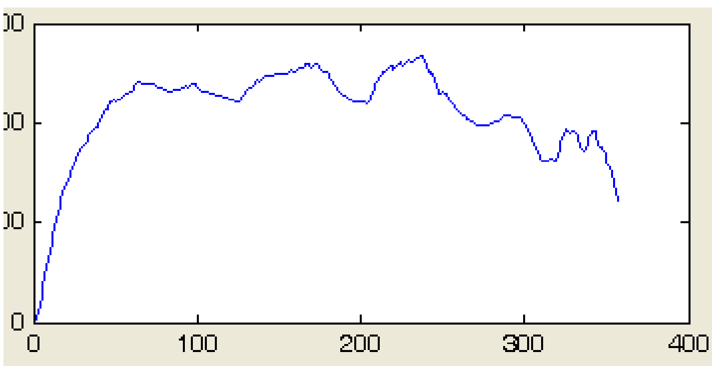


Figure 5.5: The Spectrum of a Mineral

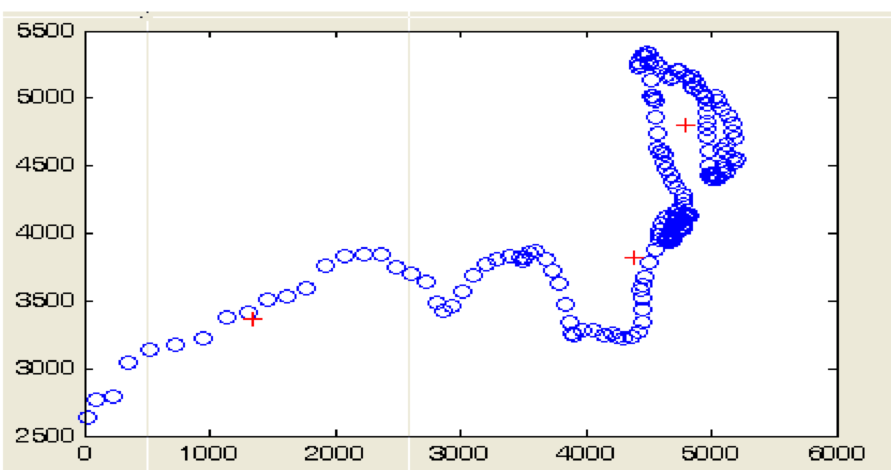


Figure 5.6: Clustered Image of a Mineral with 3 Cluster Centres Shown in Red

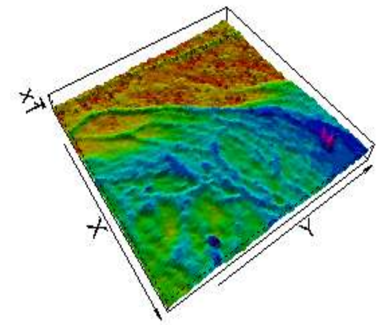
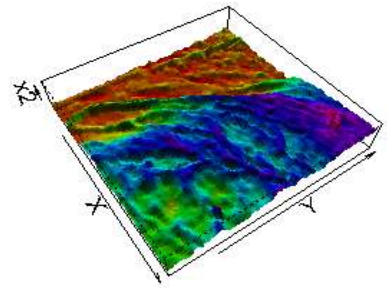
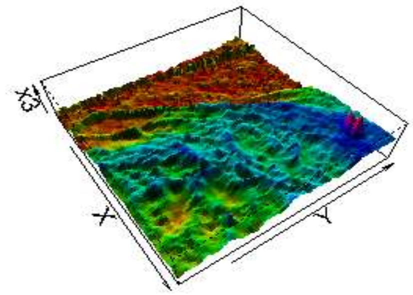
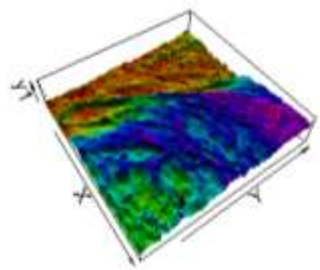
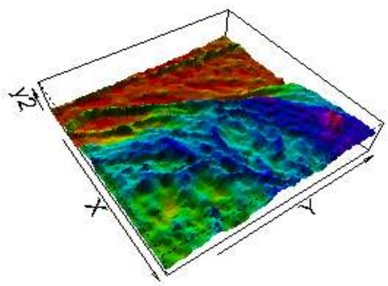
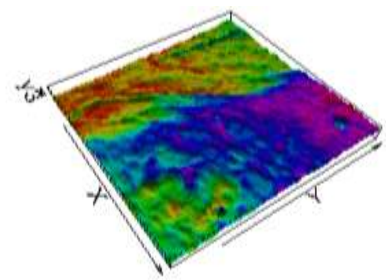
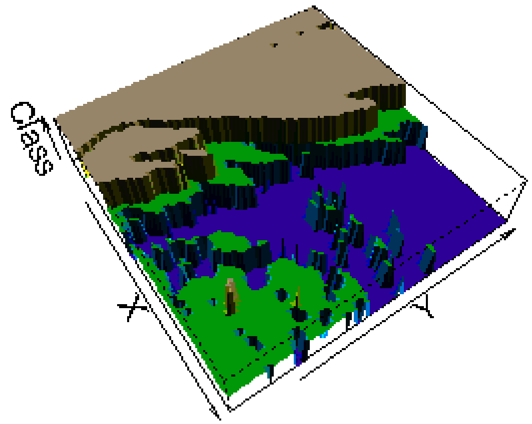
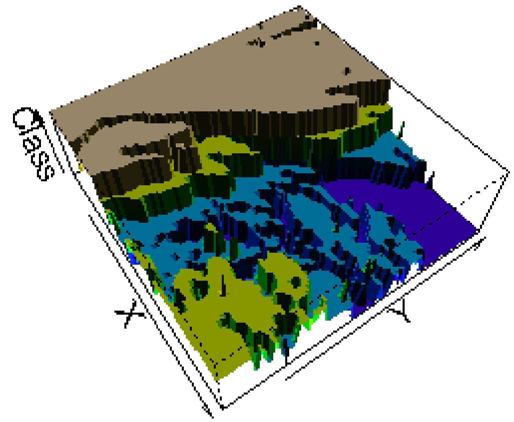
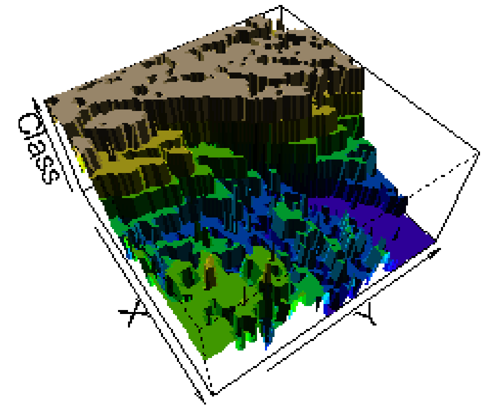
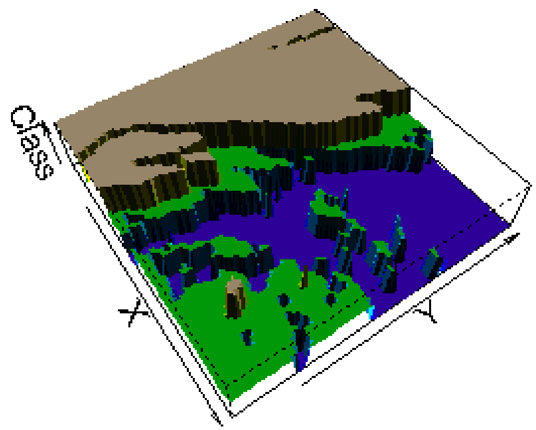
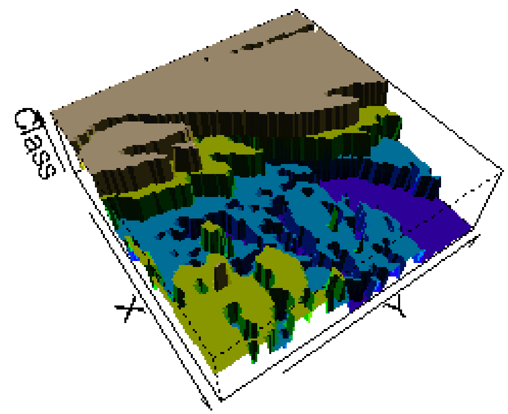
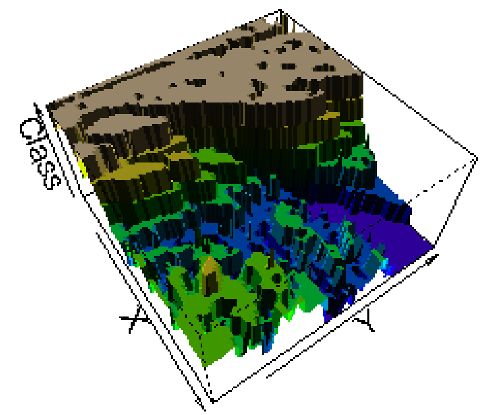
CLUSTER CENTRE		
1	2	3
		
		

Figure 5.7: 3D Plots of the Cluster Centre Image

	PREDICTED MINERAL MAP		
	3 classes	**4 classes**	**6 classes**
CC1			
CC2			

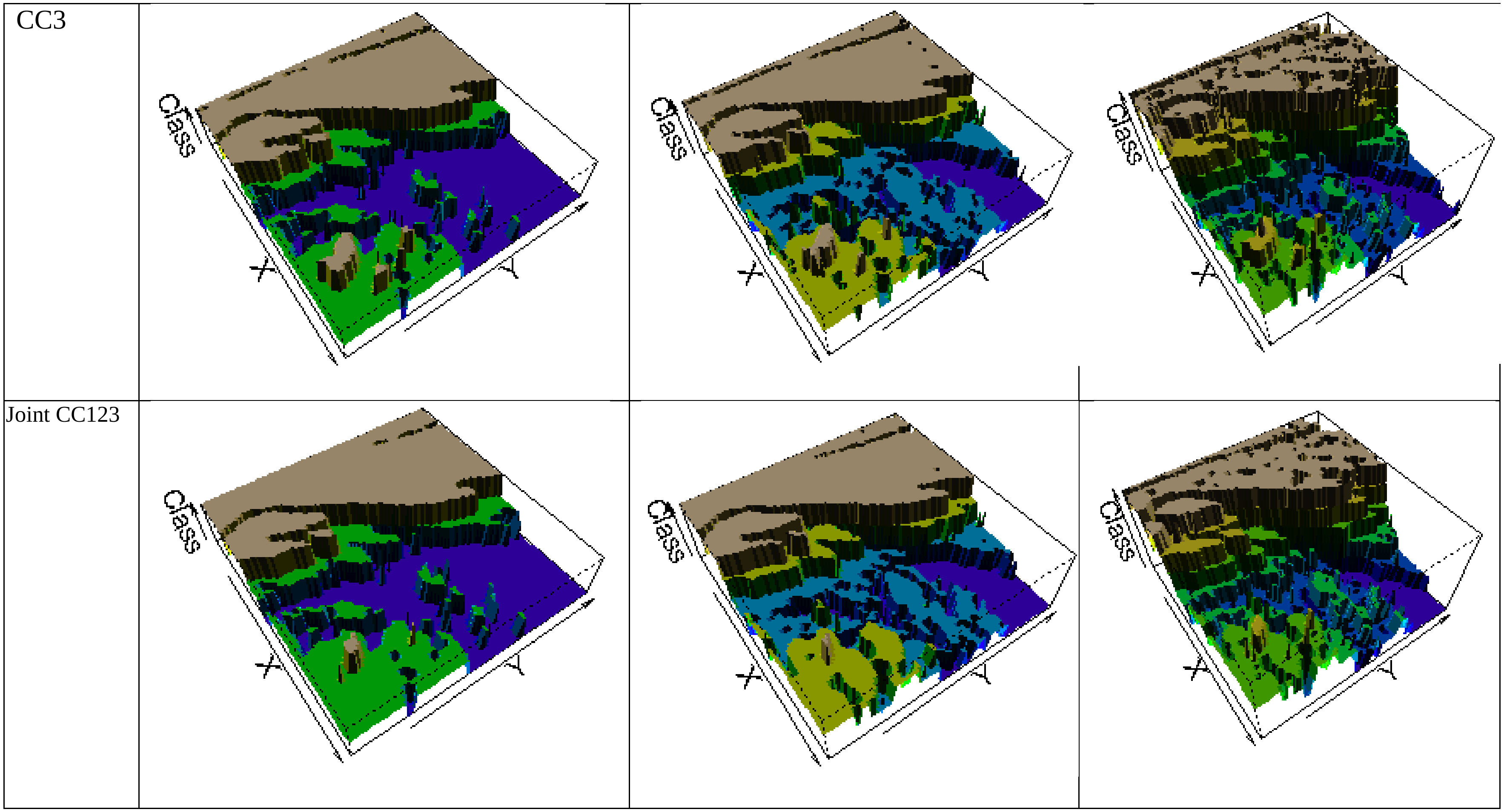


Figure 5.8: 3D Plots of the Predicted Mineral Maps

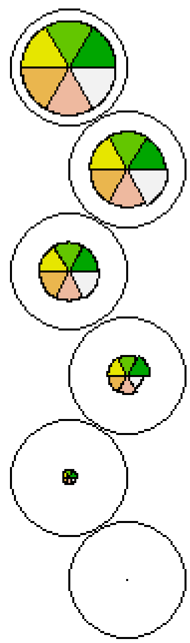


Figure 5.9: Plot of Learning of SOM

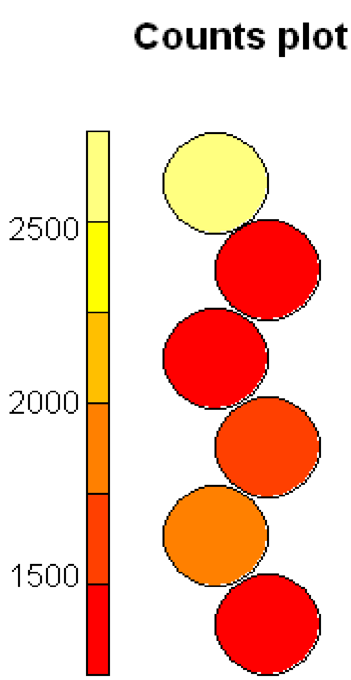


Figure 5.10: Class Count Plot of Trained of SOM

Supervised learning with ANFIS

Furthermore, we wish to create a system that learns to recognize classes of mineral with time as discussed under system design. The test of this methodology was carried out by using a modified ANFIS network to learn to classify minerals overtime. The ANFIS network consists of six input nodes and one output node as shown in figure 5.11. The cluster centre coordinated data of known mineral library were used as input. The scheme of the network is shown in figure 5.12. The question arises as to optimum choice of the number of membership functions required. We wish to minimize the number of membership functions so as to reduce the size of our network. But the initial test runs show that two membership functions do not suffice as the network did not converge and miss most of the targets during tests as shown in the comparison figure 5.13. Therefore we have to use three membership functions, and henceforth we shall discuss the results for the network with three membership functions.

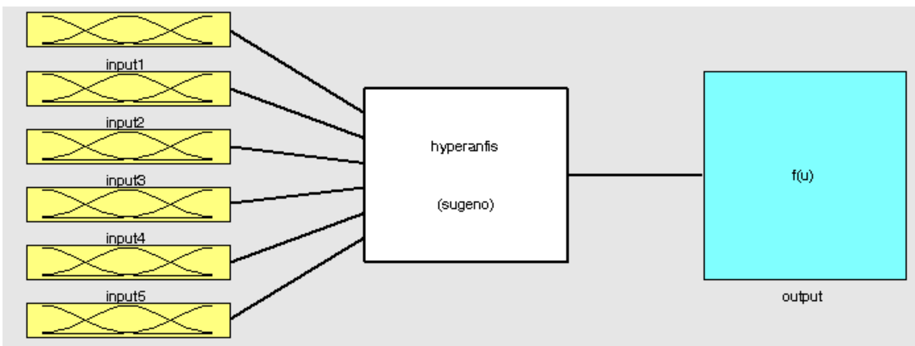


Figure 5.11: Scheme of the ANFIS network

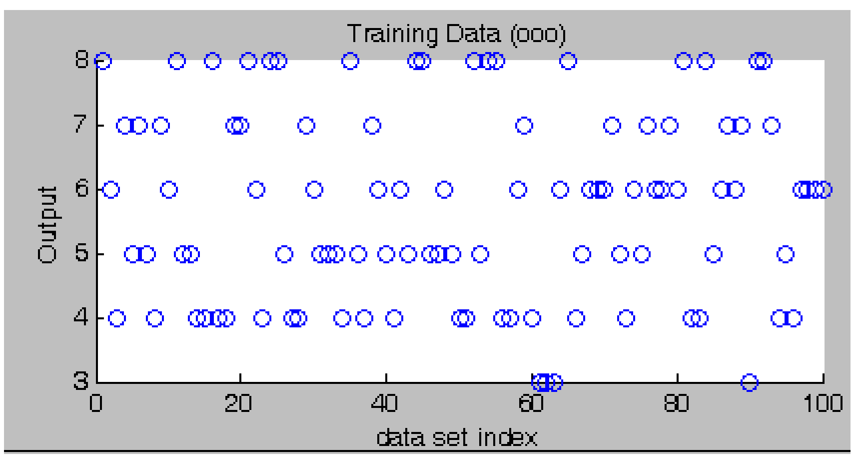


Figure 5.12: Training data set for ANFIS network

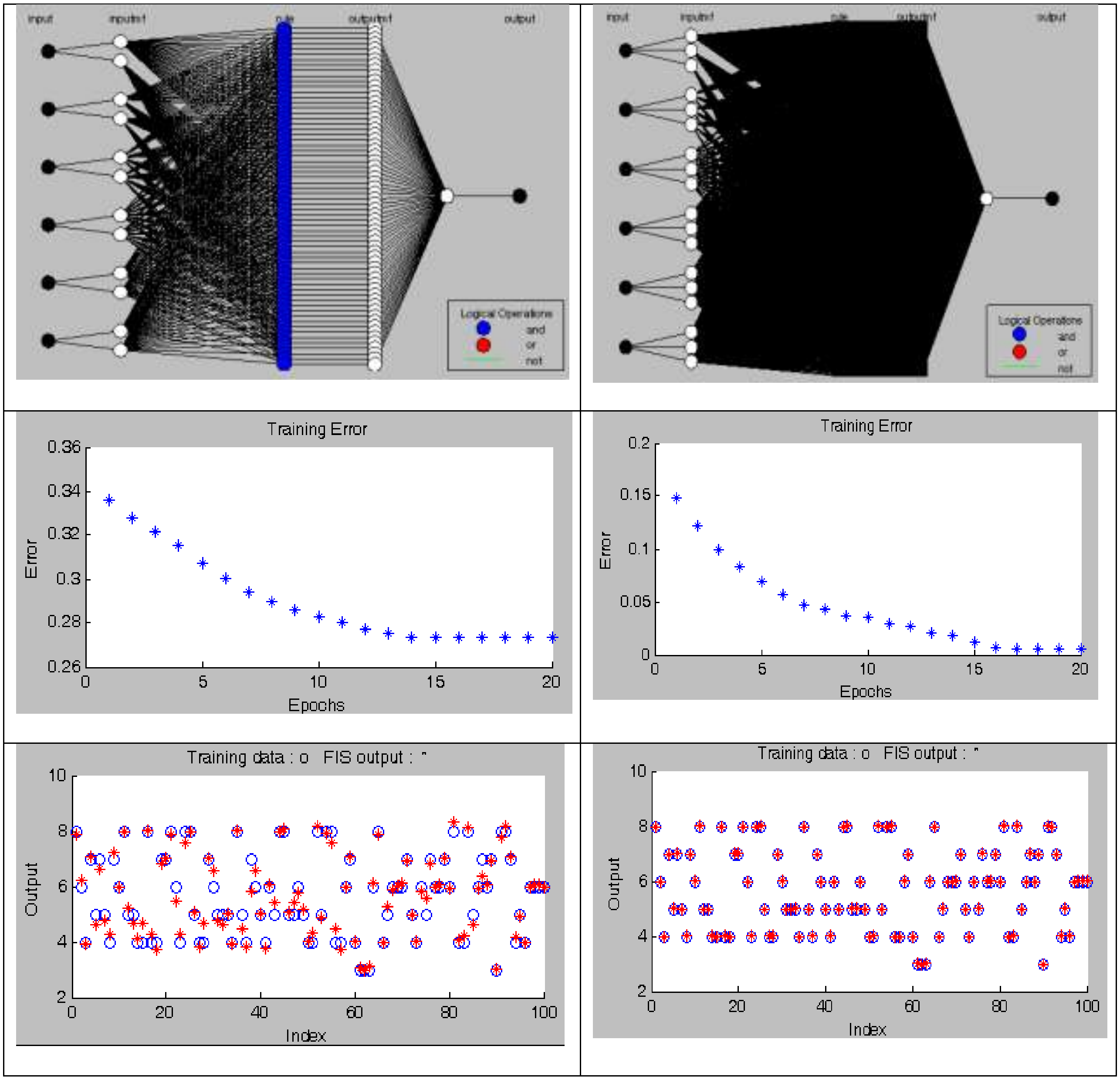


Figure 5.13: Comparison of performance of ANFIS network with 2 or 3 membership functions

With three membership functions, the network learnt to classify the samples with approximately zero error level within 20 epochs as shown in figure 5.13. Test with original training sample shows a 100% score as shown by all the red marks inside blue in figure 5.13.

Novel mineral

In figure 5.13, it can be noticed that minerals in a particular class are aligned on a straight line. If a sample for a novel mineral (not yet learned mineral) is presented to the network, the output for it will not fall on an already existing line. This is an indication that the presented sample is a novel mineral. In such case, further samples need to be presented and the system allowed to learn the new sample.

The ANFIS network learns and store knowledge as rule base. This rule base can be variously visualized as shown in figure 5.14 or as rule surfaces that shows how inputs combine with one another as shown in figure 5.15. Also the shape of the membership functions change as the system learns as depicted in figure 5.16.

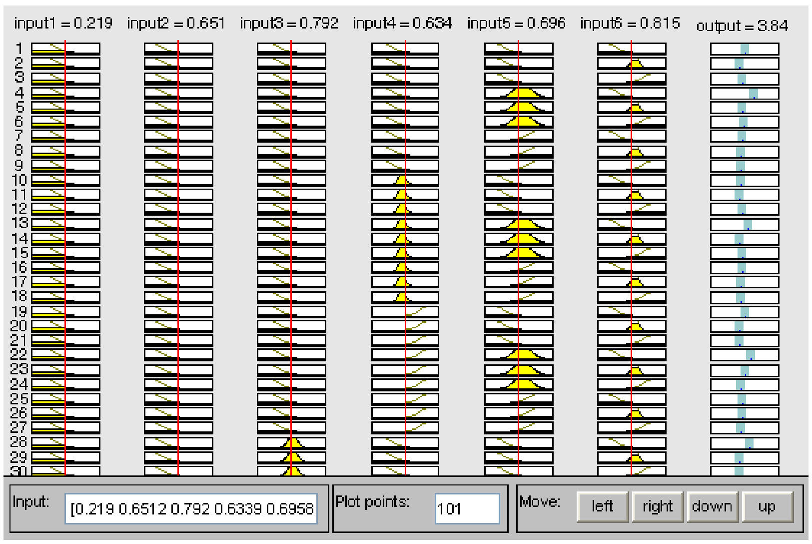
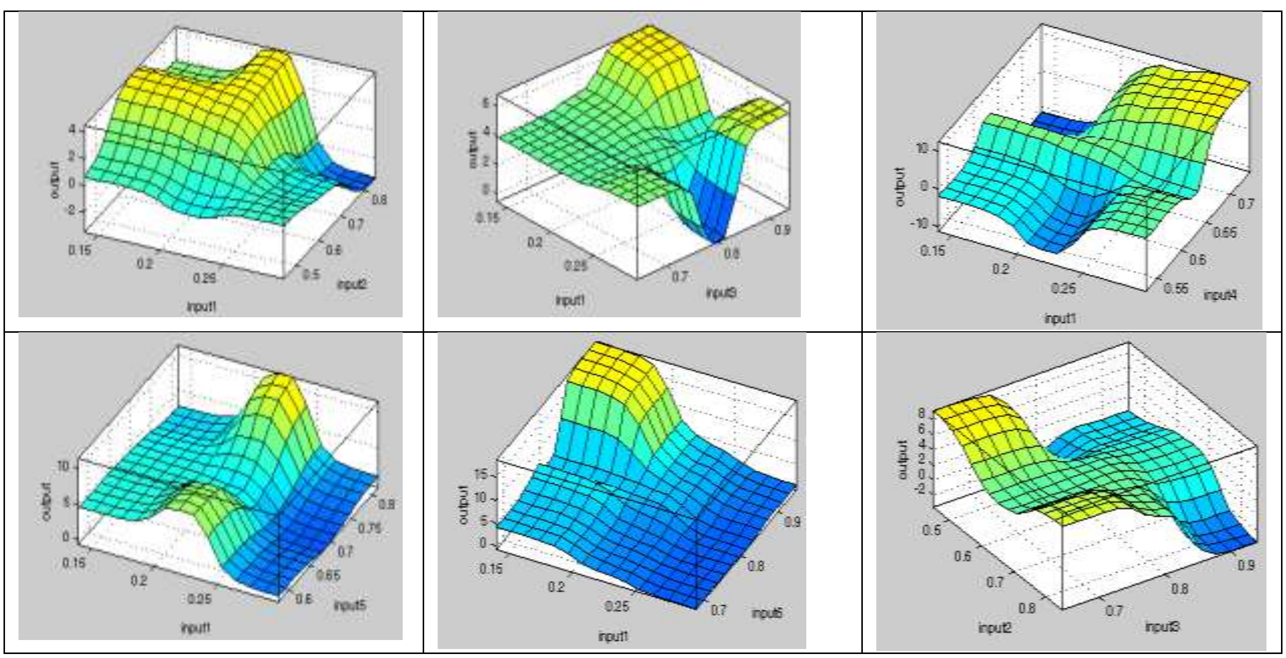


Figure 5.14: Rule base of the trained network



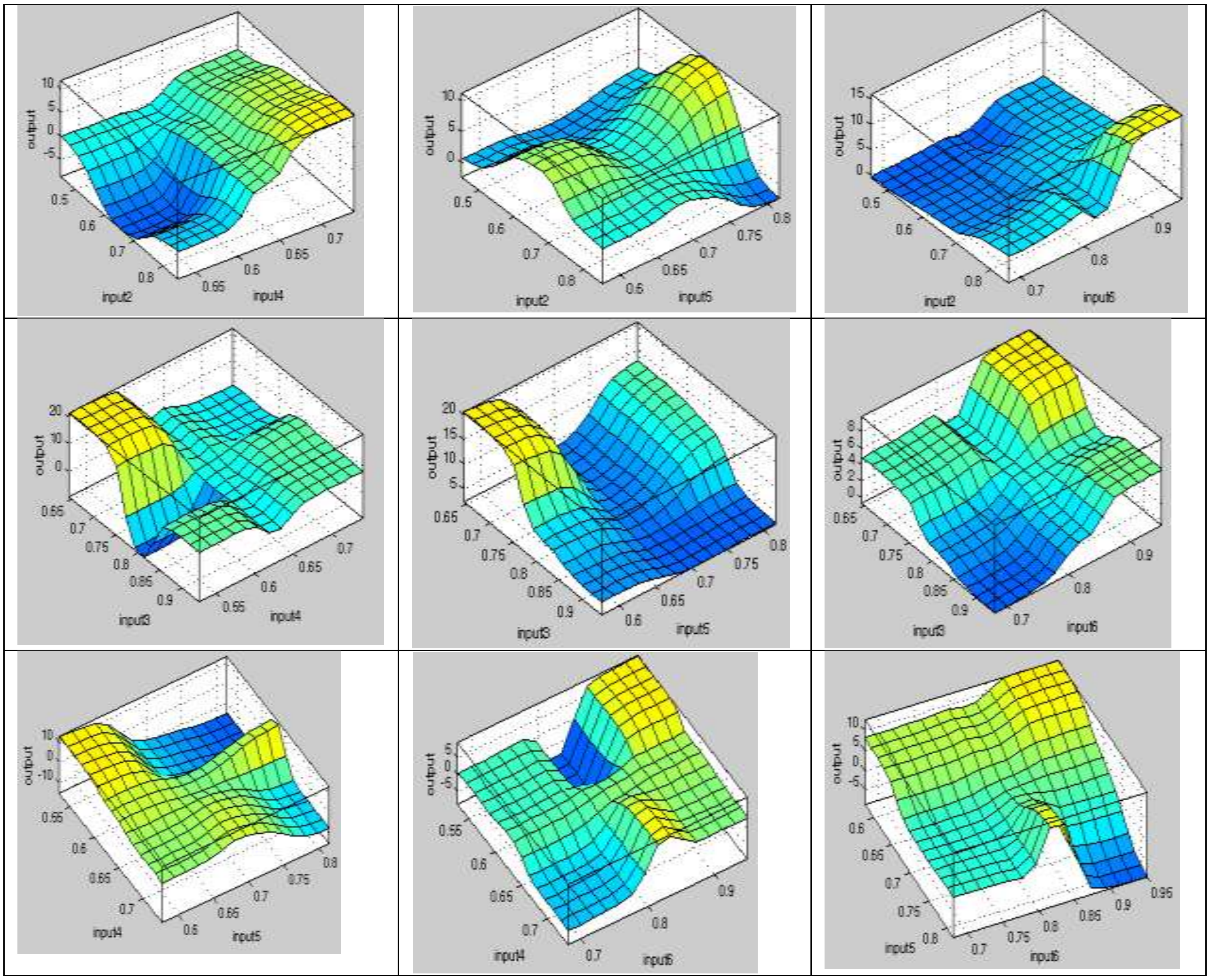
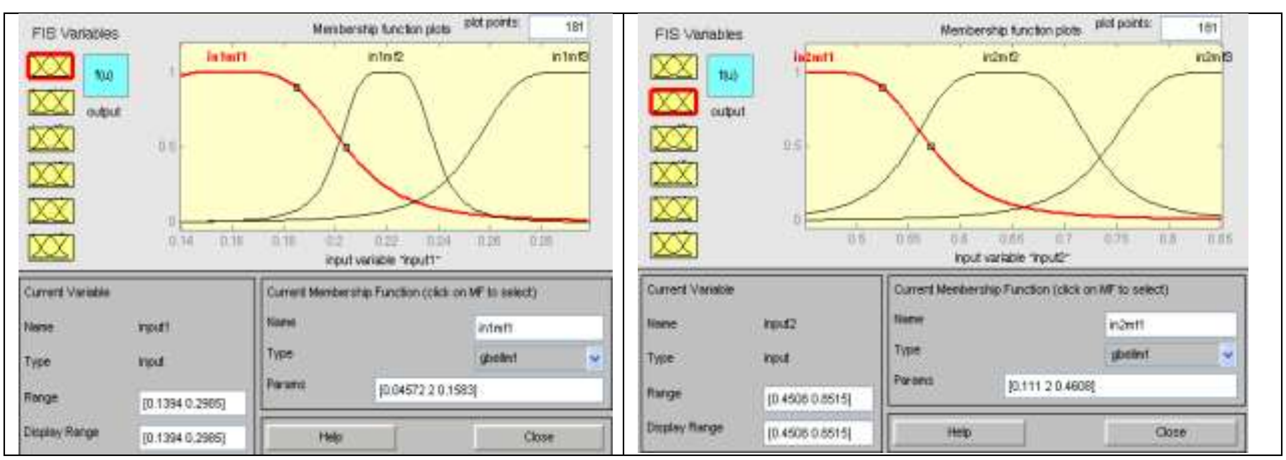


Figure 5.15: Rule surfaces of the trained network



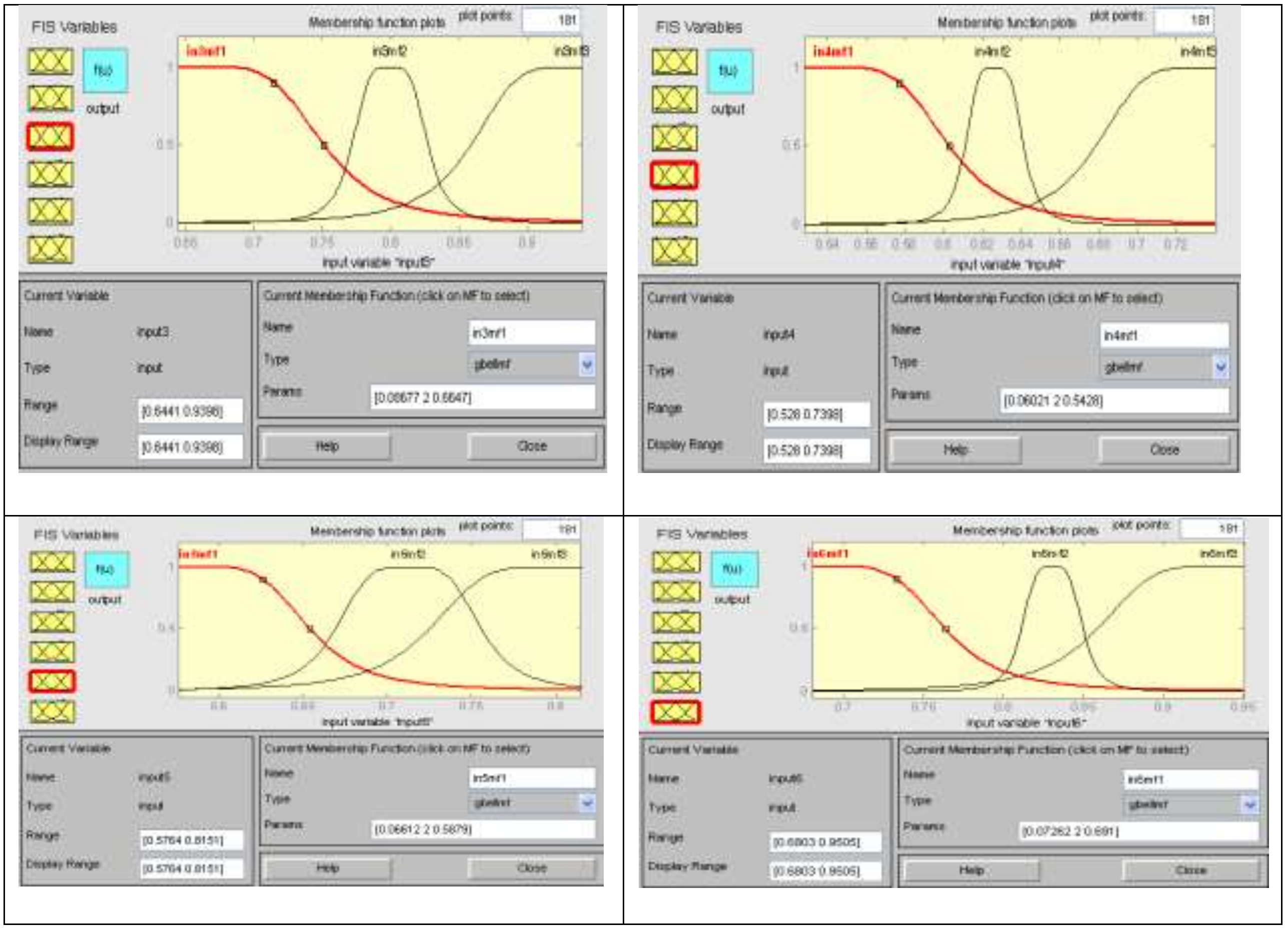


Figure 5.16: Membership functions of the trained network

Mineral Reserve Estimation

Subsequent to the detection and identification of a particular class of mineral, it is desirable to estimate the level of availability of such mineral in the given area. In particular, the abundance of such mineral in the given area needs to be measured. This information is important as it will form the basis for further prospecting works in the given area. The initial estimate must justify the investment required for further search for the mineral. Thus our task is to develop an algorithm capable of estimating the level of abundance of the detected mineral.

In this task, we proceed as follows: the class of mineral represented by each mineral is available from the classification and identification data. Thus, one can count the number of pixels that belong to a particular class of mineral in a given area. The count is then taken as a percentage of the total number of pixel in the given class divided by the total number of pixel in a given area.

Reserve estimate count = No. of pixel in a class/Total no. of mineral in the area X 100%

The result of the reserve estimation at some classes are shown in figure 5.17 to 5.19 for 3,4 and 6 classes respectively.

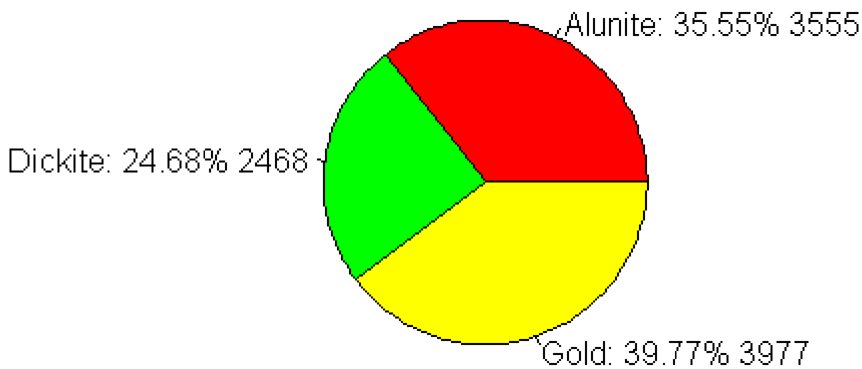


Figure 5.17: Abundance Estimate for 3 Classes

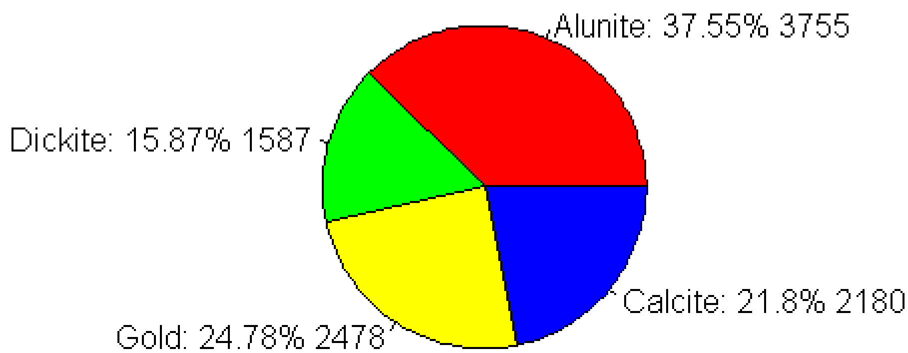


Figure 5.18: Abundance Estimate for 4 Classes

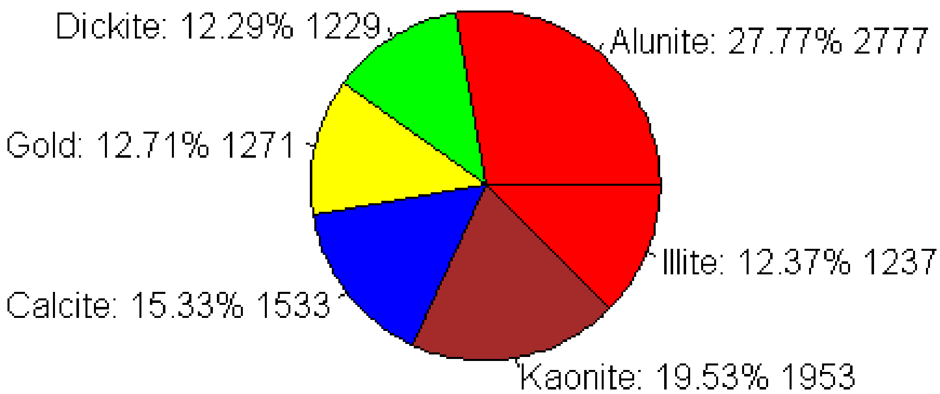


Figure 5.19: Abundance Estimate for 6 Classes

5.6 System Security

The system is secured with password. The password is OLANLOYE. This is to ensure that unauthorized users have no access to the system.

5.7 Users Guide

To run the software, the following steps or instructions should be followed:

1) Switch on the system
2) Upon successful boot, run RStudio/ R Shell to open R environment
3) For user authentication, use OLANLOYE as password
4) Select OK to open the software
5) Start hyperspectral mineral software by loading the RScript file for the software
6) Run the script to open the interface window for the system
7) Click the appropriate button (Menu) to run different functions in the system e.g. load, viewing data e.t.c.
8) Press quit button to close the system.

5.8 Hosting on the Internet

R is directly connected to the internet by using RSVG (R vector Graphics) == HTML and the output can be hosted on the internet.

5.9 Maintenance

Continuous running the program with hyperspectral data set from different location is a way of updating the database of the system with different novel minerals which the system may come across. This gives the system the opportunity to learn more and recognize varieties of mineral in future.

Though, there are different Anti Virus software in the market, an efficient Anti Virus software should be put in place to avoid virus infection.

The system is implemented with a very flexible programming language. This is to pave way for further and regular updating so as to enhance the system's performance.

CHAPTER SIX

6.0 SYSTEM TESTING AND EVALUATION

6.1 TEST PLAN

The test plan involved gathering data (hyperspectral data) of different set from the same location. The minerals present were located which were found to be the same set of minerals in the region with the inclusion of some noble mineral.

Furthermore, some expert in the field of geology, mining engineering, geophysics were asked to observe how the system works and they passed satisfactory comments.

6.2 TEST DATA

Testing in computational intelligence systems: Computational intelligent systems derive decisions from numerical data. Testing in such a system not only covers the flow and processing of data, but also the validation and verification of the processing algorithms for stability, consistency, effectiveness and efficiency. So, we have been able to test the algorithm with the same approach. The result obtained was quite acceptable. The result shows that the system is stable, consistent, effective and efficient in terms of its performance. Some of the result obtained are displayed in figure 6.1 to 6.4

Apart from testing the system based on the performance of the developed algorithm, we also made an attempt to test the system based on the various minerals available at different locations in Navada USA. The system was tested with hyperspectral data collected from each of the locations and the result shows that the newly developed system identified same type of mineral existing in each of location. Table (6.1) shows the comparison between the expected mineral (existing ones) and actual mineral (identified by the new system). The new system also identified some novel mineral as showed in serial number 2 and 4 in the table 6.1.

S/N	Location /source of data	Actual Result from the new system	Expected Result from existing system	Evaluation	Overall rating of the new system
1	Beast Lynn District	Gold (30%), Aluminum (40%) Zinc (30%)	Gold (30%) Aluminum (39%) Zinc (31%)	A = 100% B = 98%	Excellent
2	Afgon Antelop District	Silver (40%), Copper (30%), Silicon (20%) Aluminum (10%)	Silver 48%, Copper (30.5%), Silicon (21.5%)	A = 100% B = 98%	Excellent
3	Weepash Weepash District	Diamond (46.25%), Copper (28.75%) Bauxite (25.00%)	Diamond (46.50%), Copper (28.50%) Bauxite (25.0%)	A = 100% B = 98%	Excellent
4	Tonopash Divide District	Clay (13.35%), Zinc (40.62%), Iron (30. 21%), Dikite (15.82%)	Clay (14.68%), zinc (45.32) Iron (40.00%)	A = 100% B = 98%	Excellent
5	Tip Tip Fish lake valley	Cement (24.12%), Clay (28.56%) Diamond (23.32%), Silver (24%)	Cement (20%), clay (27.65%) Diamond (23.35%), Silver (29.00%)	A = 100% B = 98%	Excellent

Table 6.1 Evaluation of the System Performance

Key:

A: is used to evaluate the system based on the number of minerals it can identify.

B: is used to evaluate the new system based on its ability to determine the quantity of mineral in each location.

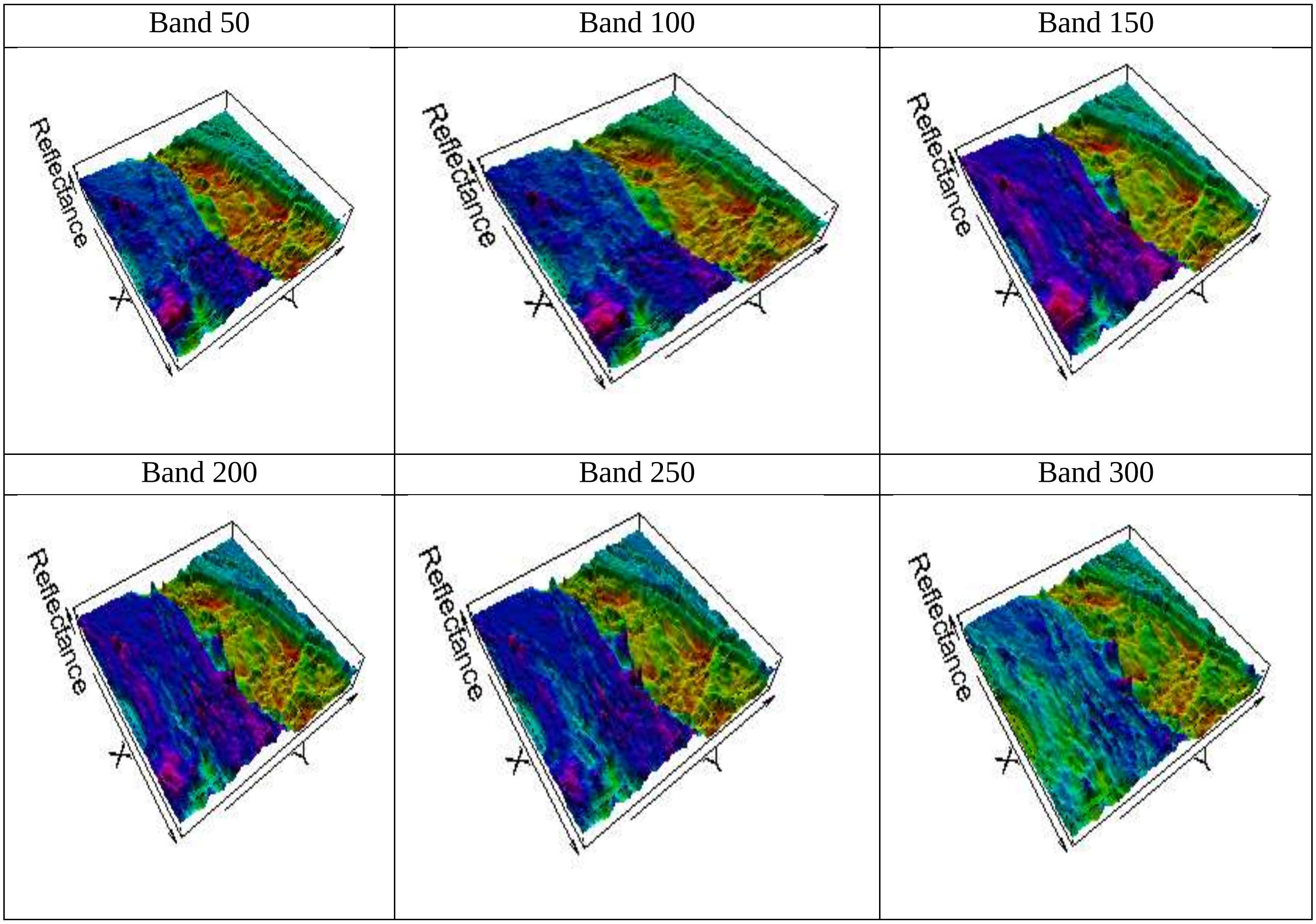


Figure 6.1: 3-D plots of input reflectance

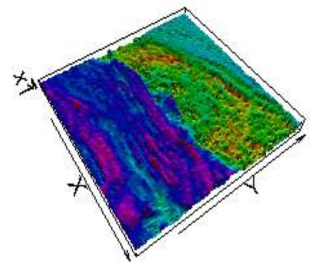
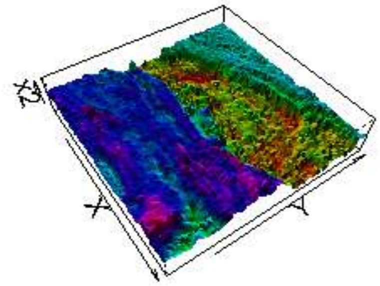
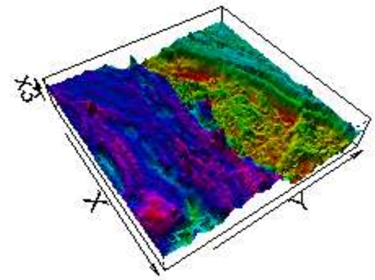
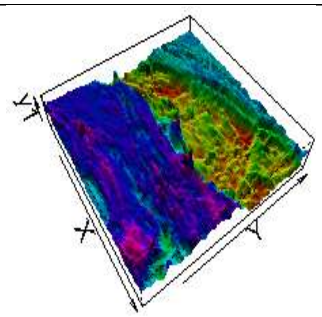
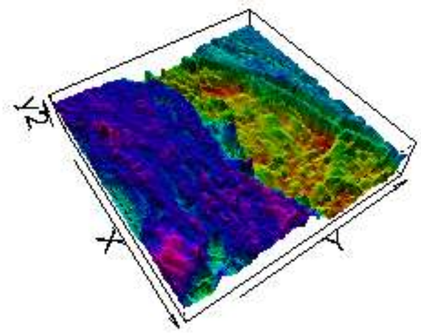
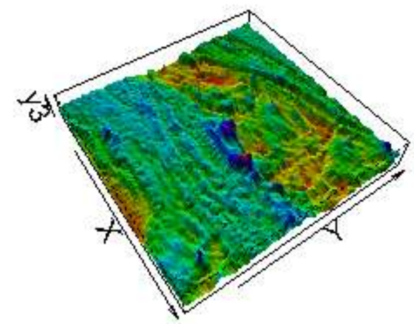
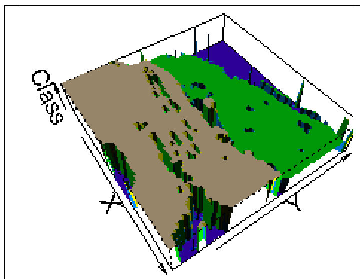
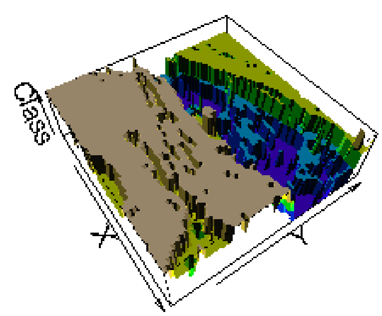
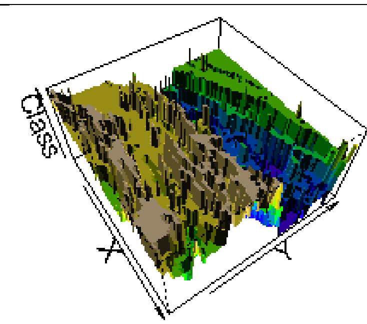
	1	2	3
X			
Y			

Figure 6.2: Spectrum cluster centre

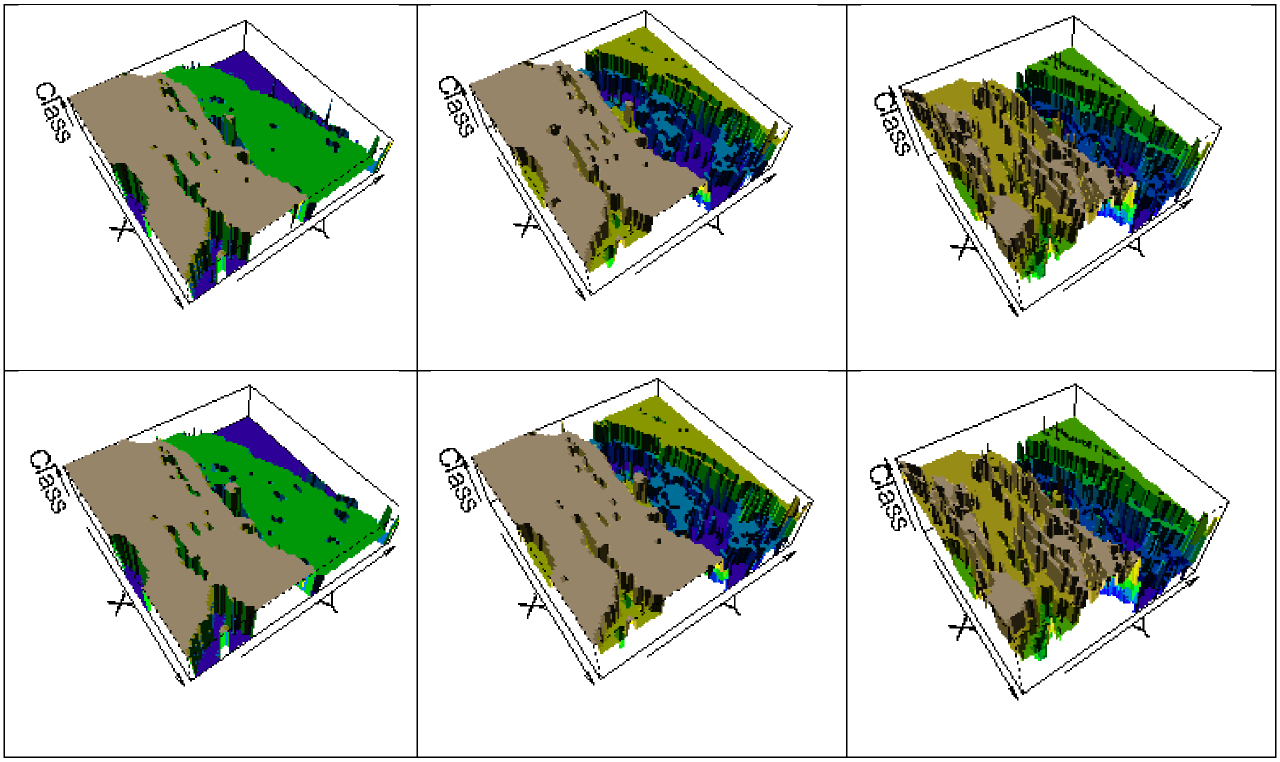


Figure 6.3: Predicted Mineral Map

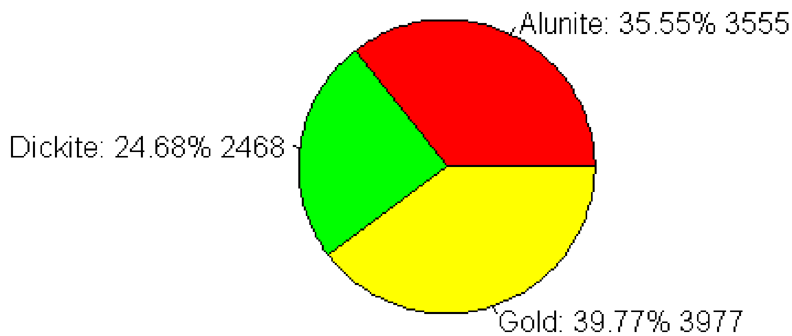


Figure 6.4: Abundance estimate for 3 classes

Again, effort were made to compare the result obtained with that of the mineral map produce by the geology and the performance of the new system was quite impressive.

Actual Versus Expected Test Result

With table 6.1, there was strong agreement between the actual test result and the expected test results. Most of the mineral located by the developed system were the same with that indicated on the mineral map of the region except that the developed system also detected some novel minerals which were not indicated by the expert. Also, result obtained in table 6.1 like comparing the actual and expected result rated the system as an excellent one.

6.3 PERFORMANCE EVALUATION

With the level of agreement between the actual test result and the expected result standing at 99%, the performance of the system is rated high. In other words, the input data set generated the expected result.

6.4 LIMITATIONS

In this type of research, there are certainly some constraints some of them includes:

1. Hyperspectral data are not readily available in Nigeria and some other countries.

2. The more the number of clusters, the more unstable is the cluster centres. This limits to some extent the capability of the system.

3. Some countries with hyperspectral data are feeling reluctant to release it. Simply because it is being commercialized. This means that they expect the user to pay certain amount of money before it can be released.

CHAPTER SEVEN

SUMMARY AND CONCLUSION

7.1 SUMMARY

Satellites were launched by different countries all over the world. One of the major advantages of satellite is that it made hyperspectral data or image available. A lot of useful information could be obtained from such data or image. In this research work, an intelligent geoinformatics system for mineral prospecting has been developed, making use of AI and image processing principles. In the process of the development, in some cases new algorithms were introduced and in other cases the exiting algorithms were modified.

One of the major problems of hyperspectral data is that it is of high dimension. This makes it too large for processing. New halving algorithm was introduced to reduce the size of complex hyperspectral data to a reasonable size that will allow for further processing of the data without losing part of information contained. We made use of clustering algorithm to cluster the hyperspectral data set. Based on the cluster centre, we used unsupervised learning algorithm to classify the mineral into various classes. If the supervised algorithm is provided with enough testing and training data of spectral library of known mineral, and it has received adequate training, it interacts with unsupervised learning algorithm to identify by name, each of the classes of the mineral earlier identified. The algorithms again were able to calculate the ratio of number of pixels in each class to the total no of pixels in that location thereby giving an estimate value of the amount of mineral in each class. The result obtained will represent the amount or volume of mineral in each of the classes.

The system was tested in the area of mineral prospecting making use of hyperspectral data set from Nevada, USA. It was able to carry out data reduction, classify various minerals at the location, identify each of the classes by name and also detect the noble minerals. The results were compared with that of the expert in Geology/geoinformatics and found to be quite satisfactory.

Though, we have applied the system in the area of mineral prospecting, but the system is flexible and with simple modification, it can still be applied in some other areas of geoinformatics e.g. soil classification, land topography and vegetation identification,

In conclusion, this is the first time an intelligent system is developed using the principle of Artificial Intelligent to solve geoinformatics problems in the area of mineral prospecting as a contribution of computer scientist toward the development of the mining industry.

7.2 REVIEW OF ACHIEVEMENTS

An intelligent geoinformatics system for mineral prospecting has been developed. The system is able to identify classes of minerals and estimate the quality of minerals in each of the classes. Novel classes of minerals can also be detected. The system has been tested and found to perform better than experts in the area of geology/geoinformatics in terms of mineral location and prospecting. Apart from applying the system in the area of mineral prospecting, the system can also be applied to solve other problems in the area of geoinformatics and again the system can also be implemented with hyperspectral data from any location of interest. Other achievements include:

(i) The system made use of computer science precisely the principle of AI and image processing to solve geological/geoinformatics problems.

(ii) A full automated system that can be used to detect type and quantity of minerals in a particular location was developed. It is also possible for the system to detect new classes of minerals (novel minerals)

(iii) The new system allows the user to have the knowledge of mineral distribution in a particular location in the whole world without leaving his /her bedroom

(iv) The developed system made the best use of satellite where hyperspectral data is made available.

(v) With the development of this system, a lot of money being spent by the mining industry on the process of locating or detecting minerals and determining whether the amount of mineral presently available will be sufficient enough for mining is reduced to the barest minimum. Hence the system aids the development of mining industry, providing job opportunities and improves the standard of living.

(vi) With the use of the system, casualties / death rates being recorded during the process of mineral location are reduced barely to the minimum.

(vii) Though mineral prospecting was used as the case study, the system can still be applied to solve some other problems in geoinformatics such as detecting different types of soil, topography and vegetation.

(viii) The system has introduced a new method of reducing high dimension of hyperspectral data to a reasonable size that will be acceptable for further processing.

(ix) It has introduced another method of image processing into the development of an intelligent system to solve geological problem.

(x) The system has introduced a new method of linking a supervised learning algorithm and unsupervised learning algorithm to carry out an effective hyperspectral data classification and identification.

(xi) The system has been able to develop an intelligent system to solve a non-linear problem in the area of geoinformatics

7.3 AREAS OF APPLICATION

The developed system is applicable in different areas:

(i) It is applicable in the area of mining and geological industry when they are interested in determining the types and quantity of minerals that are present in a particular location.

(ii) Workers in Federal Ministry of Mineral Resources will also find the system very useful since the system will provide for them, different minerals and quantity that are present at different location in their country. Such information will be of great assistance in developing mineral map of the country.

(iii) Computer Scientists who are interested to carry out further research work in the area of AI, Neurofuzzy, image processing of hyperspectral data , Data Mining, and some other related area will find the system very useful.

(iv) Computer scientists who might be keenly interested in using AI algorithms to solve some other real life problems will find the system very useful.

(v) Computer scientists who are interested in developing an intelligent system for signals processing which involves a large amount of data will also find the system very useful.

7.4 MAJOR CONTRIBUTION TO KNOWLEDGE

Though different methods have been used to solve different problems in the area of geoinformatics, this is the first time an intelligent system that can solve various geoinformatics problem was developed using AI principles. Apart from applying the system in the area of mineral prospecting, the system will still be useful in the area of soil vegetation, land topography identification. The research work also contributed to knowledge in the following ways:

(i) In the recent times, researchers have used different approaches to reduce the high dimension of hyperspectral data to a reasonable size that will be acceptable for further research work. In this research work, a new method of reducing the high dimension of hyperspectral data (called halving algorithm) has been introduced by our intelligent system.

(ii) Though, there are different types of minerals available in the list of geologist, other mineral continues to form from time to time. The existing intelligent systems were not able to detect those minerals. The newly developed intelligent system unlike the existing systems will automatically detect novel (unknown) minerals in an hyperspectral data set. Currently formed mineral and those yet to be formed in the future can easily be detected with this Intelligent System. This will not allow such mineral to waste away undetected.

(iii) This is the first time of developing an intelligent system that will enable the user to detect different types and quantity of minerals in a given hyperspectral data set from any part of the world without necessarily travelling down to the place of location.

(iv) There are different intelligent systems in existence, but the newly developed system is unique in the sense that for the first time, the system was able to make unsupervised and supervised learning algorithm to interact with each other to carry out effective hyperspectral data classification and identification.

7.5 SUGGESTIONS FOR FURTHER RESEARCH

(1) An intelligent system that can predict the quantity of mineral that is likely to be formed some years to come can be developed.

(2) A web based or an online intelligent system for mineral prospecting can still be developed.

(3) A robot system for mineral prospecting can be sent to take samples of minerals from different locations.

(4) A geoinformatics mobile intelligent system for solid mineral prospecting can still be developed.

7.6 RECOMMENDATIONS

(1) During this research work, it was discovered that some countries especially in the Africa Sub region are yet to launch their satellites. The government of such countries should embark on the process without further delay to enable the country benefit from the product of this research work.

(2) It was also discovered that hyperspectral data are not available in some countries despite the fact that there is an existence of satellite. For example, though, Nigeria launched her satellite some years ago yet, hyperspectral data is not available. The process of making hyperspectral data available should be embarked on without further delay.

(3) Government, most especially in the Sub-African continent should encourage more people to be computer literate so that they can have the opportunity of using this type of system.

(4) Geologist, Geophysist and some other professionals in mining industries should embark on the use of the new system to aid their profession and to reduce the level of casualties recorded during the process of mineral location.

(5) Expert in artificial intelligent should be encouraged to go on further research in the field of mineral prospecting.

(6) Computer scientist should make effective use of this research as a platform to carry out further research in the area of AI and hyperspectral data processing.

7.7 CONCLUSION

An intelligent geoinformatics system has been developed to solve geological problem. The system was designed and implemented using AI principles. The system was tested with series of hyperspectral data set from Nevada in USA. The result obtained indicated that the system actually perform up to expectation in the area of reducing the size of an hyperspectral data to a reasonable size, detecting the classes of minerals that are present in a particular location, identifying the type of mineral in each class as well as detecting the novel mineral in a given hyperspectral data. Though we have applied the system in the area of mineral prospecting, with simple modification, it can still be used to solve some other geoinformatics problems.

The IGSMP developed can be of great assistance in mining and related industries. If different minerals are located and explored, then the mining industry will be boosted. A lot of jobless hands will be employed most especially in the Africa–Sub-region. This can increase the standard of living and drastically improve the economy of the country.. This can be of great benefit to mankind.

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PROGRAM LISTING

R script

```
### Hyperspectral mineral mapss. Based on Tcl/Tk

#  Copyright (C) 2013 Olanloye Research
require(R.matlab)
require(e1071)
require(kohonen)
require(tcltk) || stop("tcltk support is absent")
require(graphics); require(stats)
require(spatstat)
local({
  have_ttk <- as.character(tcl("info", "tclversion")) >= "8.5"
  if(have_ttk) {
    tkbutton <- ttkbutton
    tkframe <- ttkframe
    tklabel <- ttklabel
    tkradiobutton <- ttkradiobutton
  }


  pccd<- NULL
  y <- NULL
  xlim <- NULL
  size  <- tclVar(4)
  dist  <- tclVar(1)
  kernel<- tclVar("gaussian")
  bw    <- tclVar(1)
  bcb    <- tclVar(19)
  bcc    <- tclVar(1)
  pcc    <- tclVar(1)
  cc1    <- tclVar(TRUE)
  cc2    <- tclVar(FALSE)
  cc3    <- tclVar(FALSE)
  bw.sav <- 1 # in case replot.maybe is called too early
   clascol<-c("red","green","yellow","blue","brown")
```

```
pccd <- 1:30000
dim(pccd)=c(3,10000)

plotpp <- function(arr, fct, cl, mainstr, substr, xl, yl, zl) {


  pd3=arr*fct
 # pd3=dd[,,100]*10
  nrz <- nrow(pd3)
  ncz <- ncol(pd3)
  # Create a function interpolating colors in the range of specified colors
  jet.colors <- colorRampPalette( c("blue", "red") )
  # Generate the desired number of colors from this palette
  nbcol <- 20
  if (cl==1) color <- rainbow(nbcol)
    else color <-  topo.colors(nbcol)
  # Compute the z-value at the facet centres
  zfacet <- pd3[-1, -1] + pd3[-1, -ncz] + pd3[-nrz, -1] + pd3[-nrz, -ncz]
  # Recode facet z-values into color indices
  facetcol <- cut(zfacet, nbcol)
  dev.new()

  persp(1:100,1:100,10*pd3, theta=55, phi=50, expand=0.5, col = color[facetcol], scale = FALSE,
       ltheta = -120, shade = 0.75, border = NA, box = TRUE,
       xlab = xl, ylab = yl, zlab = zl)
  title(main=mainstr, sub=substr)
}

plot3d <- function(...) {
  bc <- as.numeric(tclObj(bcb))
  v<-c("Band ", as.character(bc))
  vs<-paste(v, collapse="")
  plotpp(dd[,,bc],10,1,"3D Plot of input reflectance data", vs,
        "X","Y","Reflectance")

}

legplot3d <- function(...) {
datalegend <- colourmap(rainbow(20), breaks=seq(0,1,length=21))
plot(datalegend)
}


animate <- function(...) {
 for (i in 1:100)
   eval(substitute(image(dd[,,i],col=heat.colors(20))))

}

replot <- function(...) {


   bc <- as.numeric(tclObj(bcb))
```

```
   dev.new()

   image(dd[,,bc],col=rainbow(20))
   mr<- locator(1)
   print(mr)
   msx=floor(mr$x *100)
   msy=floor(mr$y *100)
   ddx=dd[msx,msy,1:357]
   #locator(0)
   dev.new()
   plot(ddx,type = "l")
   dev.new()
   ddxcx=ddx[1:178]
   ddxcy=ddx[179:356]
   plot(ddxcx,ddxcy)
   ddxc=matrix(c(ddxcx,ddxcy), ncol=2)
   plot(ddxc)
   cl<-cmeans(ddxc,3,20,verbose=FALSE,method="cmeans",m=2)
   print(cl$centers)
   points(cl$centers,col = "red")

}

replot.maybe <- function(...)
{
   if (as.numeric(tclObj(bw)) != bw.sav) replot()
}

regen <- function(...) {
      #dev.new()
   if (tclvalue(dist)=="1") y<<-rnorm(as.numeric(tclObj(size)))
   else y<<-rexp(as.numeric(tclObj(size)))
   xlim <<- range(y) + c(-2,2)
   replot()
}

gensom <- function(...) {
  clsize=as.numeric(tclObj(size))

  dev.new()
  split.screen(c(2, 3))
  for (k in 1:3){
   #screen(k)
   #image(ccd[,,k],col=topo.colors(20))

   yk=c(k,k+3)
   scd=ccd[,,yk]
   dim(scd)=c(10000,2)

   som.spec<- som(scd, grid = somgrid(1, clsize, "hexagonal"))
   #plot(som.spec)
   #plot(som.spec, type = "counts")
   som.prediction <- predict(som.spec,scd, scd,scd)
```

```
    pcd=som.prediction$unit.classif
    pccd[k,]=pcd
    dim(pcd)=c(100,100)
    screen(k)

    image(pcd,col=topo.colors(20))
    #plotpp(pcd,2,2)

  }

}

legpredict3d  <- function(...) {
  clsize=as.numeric(tclObj(size))
  inps=c("A","B","C","D","E","F")
  predictlegend <- colourmap(topo.colors(clsize), inputs=1:clsize)
  plot(predictlegend, col.ticks="red")
}

predict3d  <- function(...) {
  #k <- as.numeric(tclObj(pcc))
  clsize=as.numeric(tclObj(size))

  dev.new()

  yk1=NULL
  yk2=NULL
  yk3=NULL
  kc=0
  if (as.numeric(tclObj(cc1))) {
    yk1=c(1,4)
    kc=kc+1
  }

  if (as.numeric(tclObj(cc2))) {
    yk2=c(2,5)
    kc=kc+1
  }
  if (as.numeric(tclObj(cc3))) {
    yk3=c(3,6)
    kc=kc+1
  }

  yk=c(yk1,yk2,yk3)

  #screen(k)
  #image(ccd[,,k],col=topo.colors(20))

  #yk=c(k,k+3)
  scd=ccd[,,yk]
  dim(scd)=c(10000,2*kc)

  som.spec<- som(scd, grid = somgrid(1, clsize, "hexagonal"))
```

```
  #plot(som.spec)
  #plot(som.spec, type = "counts")
  som.prediction <- predict(som.spec,scd, scd,scd)
  pcd=som.prediction$unit.classif
  #pccd[k,]=pcd
  dim(pcd)=c(100,100)
  # screen(k)

  #image(pcd,col=topo.colors(20))
  plotpp(pcd,2,2,"Predicted Mineral Map","","X","Y","Class")


}

abundance  <- function(...) {
  #k <- as.numeric(tclObj(pcc))
  clsize=as.numeric(tclObj(size))

  dev.new()

  yk1=NULL
  yk2=NULL
  yk3=NULL
  kc=0
  if (as.numeric(tclObj(cc1))) {
   yk1=c(1,4)
   kc=kc+1
  }

  if (as.numeric(tclObj(cc2))) {
   yk2=c(2,5)
   kc=kc+1
  }
  if (as.numeric(tclObj(cc3))) {
   yk3=c(3,6)
   kc=kc+1
  }

  yk=c(yk1,yk2,yk3)

  #screen(k)
  #image(ccd[,,k],col=topo.colors(20))

  #yk=c(k,k+3)
  scd=ccd[,,yk]
  dim(scd)=c(10000,2*kc)

  som.spec<- som(scd, grid = somgrid(1, clsize, "hexagonal"))
  #plot(som.spec)
  #plot(som.spec, type = "counts")
  som.prediction <- predict(som.spec,scd, scd,scd)
  pcd=som.prediction$unit.classif
  #pccd[k,]=pcd
```

```
 clasc=rep(0,clsize)
# dim(pcd)=c(100,100)
 # screen(k)
 for (i in 1:10000) {
   ci=pcd[i]
    clasc[ci]=clasc[ci]+1
 }

  perclas=clasc/100
 vstr=rep("",clsize)
 for (i in 1:clsize){
    v<-c("Class ", as.character(i),": ", as.character(perclas[i]), "% ",as.character(clasc[i]))
    vstr[i]<-paste(v, collapse="")
 }
 names(clasc)<-vstr
  pie(clasc,col=clascol,main = "Abundance Volume Estimation")
 #barplot(clasc,col=topo.colors(20))
 #image(pcd,col=topo.colors(20))
 #plotpp(pcd,2,2)


}

predictsom  <- function(...) {
 #k <- as.numeric(tclObj(pcc))
 clsize=as.numeric(tclObj(size))

 dev.new()

 yk1=NULL
 yk2=NULL
 yk3=NULL
 kc=0
 if (as.numeric(tclObj(cc1))) {
   yk1=c(1,4)
   kc=kc+1
 }

 if (as.numeric(tclObj(cc2))) {
   yk2=c(2,5)
   kc=kc+1
 }
 if (as.numeric(tclObj(cc3))) {
   yk3=c(3,6)
   kc=kc+1
 }

 yk=c(yk1,yk2,yk3)

 #screen(k)
 #image(ccd[,,k],col=topo.colors(20))

 #yk=c(k,k+3)
```

```
  scd=ccd[,,yk]
  dim(scd)=c(10000,2*kc)

  som.spec<- som(scd, grid = somgrid(1, clsize, "hexagonal"))
  #plot(som.spec)
  #plot(som.spec, type = "counts")
  som.prediction <- predict(som.spec,scd, scd,scd)
  pcd=som.prediction$unit.classif
  #pccd[k,]=pcd
  dim(pcd)=c(100,100)
  # screen(k)

 image(pcd,col=topo.colors(20))
 # plotpp(pcd,2,2)


}

showsom  <- function(...) {
  #k <- as.numeric(tclObj(pcc))
  clsize=as.numeric(tclObj(size))

  dev.new()

  yk1=NULL
  yk2=NULL
  yk3=NULL
  kc=0
  if (as.numeric(tclObj(cc1))) {
   yk1=c(1,4)
   kc=kc+1
  }

  if (as.numeric(tclObj(cc2))) {
   yk2=c(2,5)
   kc=kc+1
  }
  if (as.numeric(tclObj(cc3))) {
   yk3=c(3,6)
   kc=kc+1
  }

  yk=c(yk1,yk2,yk3)

  #screen(k)
  #image(ccd[,,k],col=topo.colors(20))

  #yk=c(k,k+3)
  scd=ccd[,,yk]
  dim(scd)=c(10000,2*kc)

  som.spec<- som(scd, grid = somgrid(1, clsize, "hexagonal"))
  plot(som.spec)
```

```
}

showcount  <- function(...) {
  #k <- as.numeric(tclObj(pcc))
  clsize=as.numeric(tclObj(size))

  dev.new()

  yk1=NULL
  yk2=NULL
  yk3=NULL
  kc=0
  if (as.numeric(tclObj(cc1))) {
    yk1=c(1,4)
    kc=kc+1
  }

  if (as.numeric(tclObj(cc2))) {
    yk2=c(2,5)
    kc=kc+1
  }
  if (as.numeric(tclObj(cc3))) {
    yk3=c(3,6)
    kc=kc+1
  }

  yk=c(yk1,yk2,yk3)

  #screen(k)
  #image(ccd[,,k],col=topo.colors(20))

  #yk=c(k,k+3)
  scd=ccd[,,yk]
  dim(scd)=c(10000,2*kc)

  som.spec<- som(scd, grid = somgrid(1, clsize, "hexagonal"))
  #plot(som.spec)
  plot(som.spec, type = "counts")


}

genclust <- function(...) {
  ccd=c(1:60000)
  dim(ccd)=c(100,100,6)
  for (i in 1:100) {
    for (j in 1:100) {
      ddx=dd[i,j,1:357]
      ddxcx=ddx[1:178]
      ddxcy=ddx[179:356]
```

```
    ddxc=matrix(c(ddxcx,ddxcy), ncol=2)
    cl<-cmeans(ddxc,3,20,verbose=FALSE,method="cmeans",m=2)
    cc=cl$centers
    ccs=cc[order(cc[,1]),]

    cd=c(ccs)

    ccd[i,j,1:6]=cd
   }
  }
  showclustdata()
}

showclustdata <- function(...) {

  dev.new()
  split.screen(c(2, 3))
  for (k in 1:6){
   screen(k)
   image(ccd[,,k],col=topo.colors(20))
  }
}

showclust3d <- function(...) {
  bc <- as.numeric(tclObj(bcc))
  xy<-c("x1","x2","x3","y1","y2","y3")
  plotpp(ccd[,,bc],10,1,"Spectrum cluster center coordinates",xy[bc],"X","Y",xy[bc])
}

legshowclust3d <- function(...) {
  clusterlegend <- colourmap(rainbow(20), breaks=seq(0,1,length=21))
  plot(clusterlegend)
}

grDevices::devAskNewPage(FALSE) # override setting in demo()
tclServiceMode(FALSE)
base <- tktoplevel()

tkwm.title(base, "Mineral Hyperspec")

spec.frm <- tkframe(base,borderwidth=2)
left.frm <- tkframe(spec.frm)
right.frm <- tkframe(spec.frm)

## Two left frames:
frame1 <- tkframe(left.frm, relief="groove", borderwidth=2)
tkpack(tklabel(frame1, text="Cluster centers"))
tkpack(tkbutton(frame1, text="Generate", command=genclust))
tkpack(tkbutton(frame1, text="Show cluster data", command=showclustdata))
tkpack(tkbutton(frame1, text="Show cluster data 3d", command=showclust3d))
tkpack(tkbutton(frame1, text="Legend", command=legshowclust3d))
tkpack(tkentry(frame1, text=bcc))
```

```
frame2 <- tkframe(left.frm, relief="groove", borderwidth=2)
tkpack(tklabel(frame2, text="Kernel"))
for ( i in c("gaussian", "epanechnikov", "rectangular",
          "triangular", "cosine") ) {
   tmp <- tkradiobutton(frame2, command=replot,
                   text=i, value=i, variable=kernel)
   tkpack(tmp, anchor="w")
}

## Two right frames:
frame3 <-tkframe(right.frm, relief="groove", borderwidth=2)
tkpack(tklabel(frame3, text="No. of classes"))
for ( i in c(3,4,6,10) ) {
   tmp <- tkradiobutton(frame3, command=gensom,
                   text=i,value=i,variable=size)
   tkpack(tmp, anchor="w")

}
tkpack(tkcheckbutton(frame3, text="CC1", variable=cc1))
tkpack(tkcheckbutton(frame3, text="CC2", variable=cc2))
tkpack(tkcheckbutton(frame3, text="CC3", variable=cc3))

tkpack(tkbutton(frame3, text="Train SOM", command=gensom))
tkpack(tkbutton(frame3, text="Show SOM", command=showsom))
tkpack(tkbutton(frame3, text="Show count", command=showcount))
tkpack(tkbutton(frame3, text="Predict", command=predictsom))
tkpack(tkbutton(frame3, text="Predict 3d", command=predict3d))
tkpack(tkbutton(frame3, text="Legend", command=legpredict3d))
tkpack(tkbutton(frame3, text="Abundance", command=abundance))
tkpack(tkentry(frame3, text=pcc))

frame4 <-tkframe(left.frm, relief="groove", borderwidth=2)
tkpack(tklabel (frame4, text="Bandwidth"))
tkpack(tkentry(frame4, text=bcb))
tkpack(tkbutton(frame4, text="Plot", command=replot))
tkpack(tkbutton(frame4, text="Plot3d", command=plot3d))
tkpack(tkbutton(frame4, text="Legend", command=legplot3d))
#tkpack(tkbutton(frame4, text="Animate", command=animate))


tkpack(frame1, frame4, fill="x")
tkpack(frame3,  fill="x")
tkpack(left.frm, right.frm,side="left", anchor="n")

## `Bottom frame' (on base):
q.but <- tkbutton(base,text="Quit",
          command=function() tkdestroy(base))

tkpack(spec.frm, q.but)
tclServiceMode(TRUE)

cat("******************************************************\n",
   "The source for this demo can be found in the file:\n",
```

file.path(system.file(package = "tcltk"), "demo", "tkdensity.R"),
"\n***\n")

})

Appendix B

Program list

Hyperspec.m

```
% Hints: contents = get(hObject,'String') returns listbox1 contents as
cell array
%          contents{get(hObject,'Value')} returns selected item from
listbox1
get(handles.Fig1,'SelectionType');
% If double click
if strcmp(get(handles.Fig1,'SelectionType'),'open')
    index_selected = get(handles.listbox1,'Value');
    file_list = get(handles.listbox1,'String');
    % Item selected in list box
    filename = file_list{index_selected};
    % If directory
    if  handles.is_dir(handles.sorted_index(index_selected))
        cd (filename)
        % Load list box with new directory.
        load_listbox(pwd,handles)
    else
        [path,name,ext,ver] = fileparts(filename);
        switch ext
            case '.dat'
                % Open FIG-file with guide command.
                %guide (filename)
                X                                              =
multibandread(filename,[600,320,357],'int16',0,'bsq','ieee-le',...
{'Row','Range',[101 200]},{'Column','Range',[1 100]});
%{'Band','Direct',[1:25]}); //reading of input data
Y = squeeze(X(:,:,100)); //selection of a band
XX = double(Y)/max(max(max(Y)));//normalization of data
axes(handles.axes1)
imagesc(XX);//plotting of colormap of a band
axes(handles.axes2)
axesm gstereo;
legend=[1,30,-30];
load topo;
Zt=topo(1:100,1:100);//dem topology data
%meshm(Y,legend)
meshm(XX,legend,size(XX),Zt);tightmap;//plotting   of   dem   and   band
colormap
daspectm('m',100); tightmap;
```

```
view(20,35);
set(gca,'Box','off');
camlight;
lighting phong;
set(gca,'projection','perspective');
axis tight;
%zoom(4);
tightmap;
axes(handles.axes3)
band=1:10:350;
Y = squeeze(X(:,:,band));
XX = double(Y)/max(max(max(Y)));
%imagesc(XX);
D = Y;
[x,y,z,D] = subvolume(D,[1,80,1,80,nan,nan]);
%z=[1 10 20 30 40 50 60 70 80 90 100]';
p1 = patch(isosurface(x,y,z,D, 5),...
     'FaceColor','red','EdgeColor','none');
isonormals(x,y,z,D,p1);
p2 = patch(isocaps(x,y,z,D, 5),...
     'FaceColor','interp','EdgeColor','none');
view(3); axis tight; daspect([1,1,.4])
axes(handles.axes1)
while true
    pp=ginput(1);// selection of a pixel point from the band colormap
    cc = ceil(pp);
    Z = squeeze(X(cc(1),cc(2),:));//spectrum of the selected pixel
    axes(handles.axes4);
    plot(Z);//plot of the spectrum for the selected pixel
    d=Z;
    axes(handles.axes5);
    dd=[d(1:178) d(356:-1:179)];//transpose for characterization map
    plot(dd(:,1),dd(:,2),'o');//plot of characterization map
    hold on;
    n_clusters = 3;                    % number of clusters %[C,S] =
subclust(dd,0.5);
    [center,U,obj_fcn] = fcm(dd, n_clusters);//clustering with fuzzy
cmeans
    plot(center(:,1),center(:,2),'r+');//plot of cluster centers
    hold off;
   for i=1:100 //loop for calculating cluster center data for each
pixel
      for j=1:100
           d = squeeze(X(i,j,:));
            dd=[d(1:178) d(356:-1:179)];
             [center,U,obj_fcn] = fcm(dd, n_clusters);
              center=sort(center);
             clusterdata(i,j,:,:)=center(:,:);
        end
    end
    assignin('base', 'clusterdata',clusterdata); // saving of cluster
center data
```

```
    hypercluster;
end
```

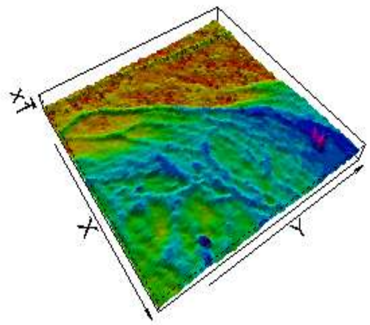
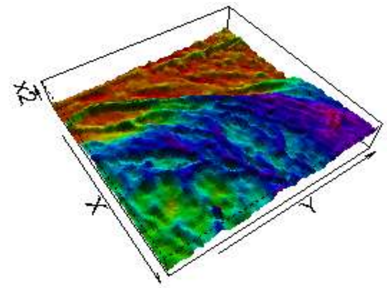
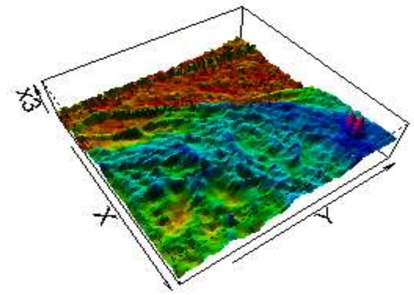
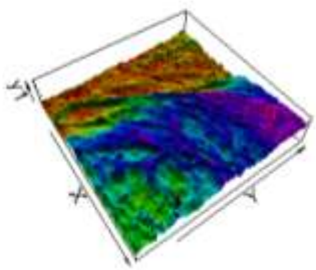
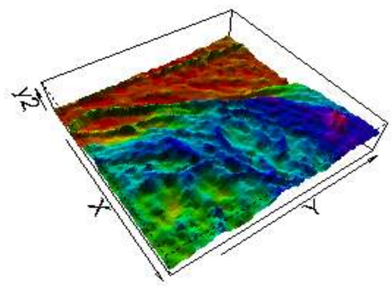
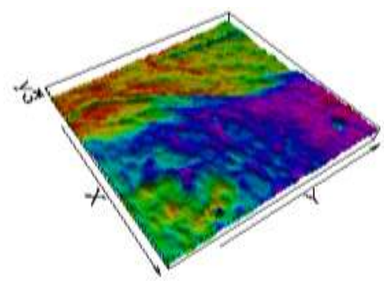
Hypercluster.m

```
%XY=evalin('base','clusterdata');
%fid = fopen('clusterdata.txt','w');
%fprintf(fid,'%g\n',XY);
%status = fclose(fid);

fid = fopen('clusterdata.txt','r'); //reading of cluster center data
XX= fscanf(fid,'%g');
XY=reshape(XX,100,100,3,2);
XY=XY/max(max(max(max(XY))));
status = fclose(fid);
axes(handles.axes1);
imagesc(XY(:,:,1,1)); //plot of cluster center data colormap
axes(handles.axes2);
imagesc(XY(:,:,2,1));
axes(handles.axes3);
imagesc(XY(:,:,3,1));
avgX(:,:)=XY(:,:,1,1)+XY(:,:,2,1)+XY(:,:,3,1);
axes(handles.axes4);
hX=imagesc(avgX); //plot of aggregate cluster center data
%save ximag.dat avgX;
axes(handles.axes5);
imagesc(XY(:,:,1,2));
axes(handles.axes6);
imagesc(XY(:,:,2,2));
axes(handles.axes7);
imagesc(XY(:,:,3,2));
avgY(:,:)=XY(:,:,1,2)+XY(:,:,2,2)+XY(:,:,3,2);
axes(handles.axes8);
hY=imagesc(avgY);
net = newc([0 1;0 1],3,.1); //structure of kohonen network
w = net.IW{1};
axes(handles.axes9);
% %P(1,:)=XY(:,:,1,1);
% %P(2,:)=XY(:,:,1,2);
% 1:10:100
x=reshape(XY(1:10:100,1:10:100,1,1),1,[]);
y=reshape(XY(1:10:100,1:10:100,1,2),1,[]);
P=[x ;y];
plot(P(1,:),P(2,:),'+r');
hold on;
circles = plot(w(:,1),w(:,2),'ob');
net.trainParam.epochs = 6;
net = train(net,P); //training of kohonen network
w = net.IW{1};
```

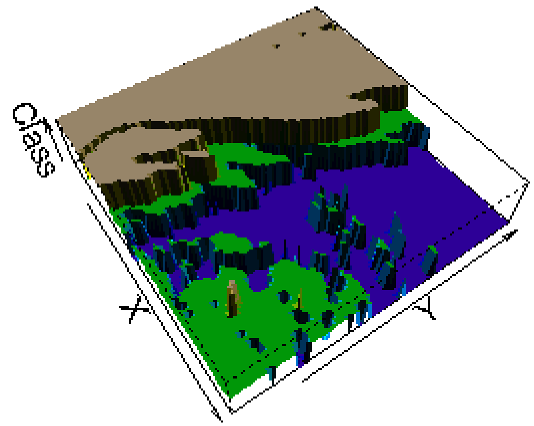
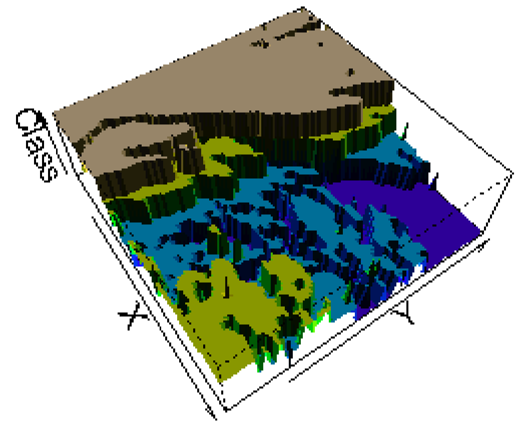
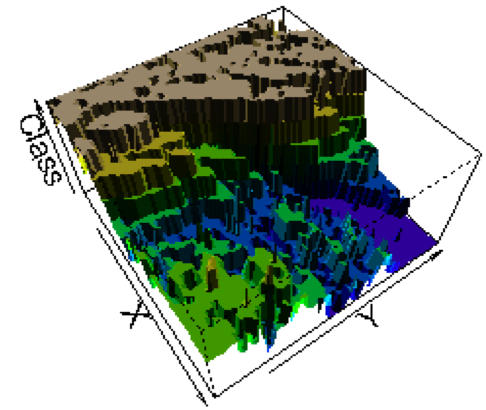
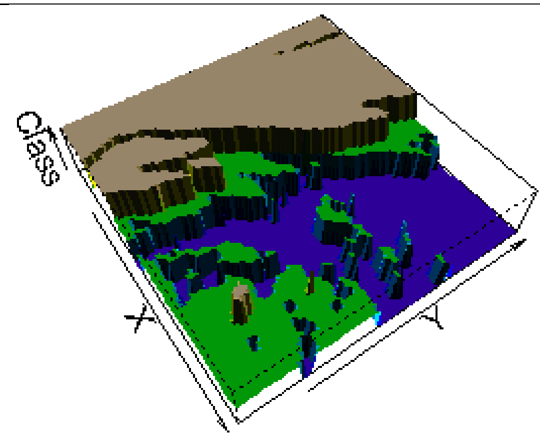
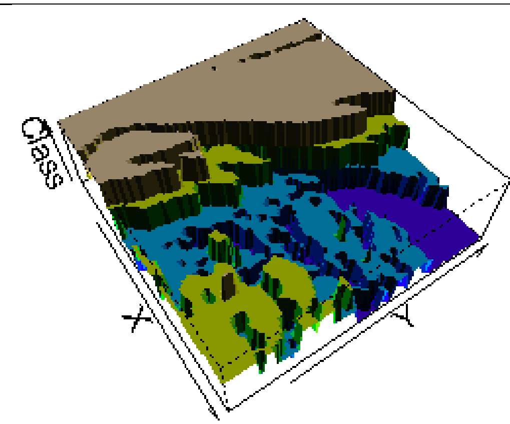
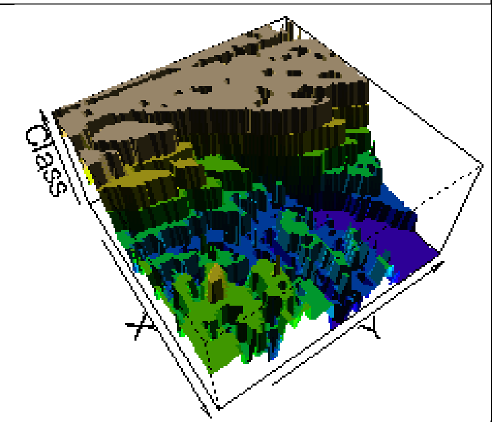
```
delete(circles);
plot(w(:,1),w(:,2),'ob');
A=[];
for  i=1:100  //loop  for  generating  classes  for  each  pixel  with  the
trained network
    for j=1:100
    p = [XY(i,j,1,1); XY(i,j,1,2)];
a = sim(net,p);
%b=a(1);
A(i,j)= vec2ind(a);
    end
end
%plot(,,'r+');
axes(handles.axes13);
imagesc(A);// plot of the output class data – mineral prediction map
B=A;

axes(handles.axes10);
% %P(1,:)=XY(:,:,1,1);
% %P(2,:)=XY(:,:,1,2);
% 1:10:100
net = newc([0 1;0 1],3,.1);
w = net.IW{1};
x=reshape(XY(1:10:100,1:10:100,2,1),1,[]);
y=reshape(XY(1:10:100,1:10:100,2,2),1,[]);
P=[x ;y];
plot(P(1,:),P(2,:),'+r');
hold on;
circles = plot(w(:,1),w(:,2),'ob');
net.trainParam.epochs = 6;
net = train(net,P);
w = net.IW{1};
delete(circles);
plot(w(:,1),w(:,2),'ob');
A=[];
for i=1:100
    for j=1:100
    p = [XY(i,j,2,1); XY(i,j,2,2)];
a = sim(net,p);
%b=a(1);
A(i,j)= vec2ind(a);
    end
end
%plot(,,'r+');
axes(handles.axes14);
imagesc(A);
C=A;
axes(handles.axes12);
plot(XY(:,:,2,1),XY(:,:,2,2),'r+');

axes(handles.axes11);
% %P(1,:)=XY(:,:,1,1);
```

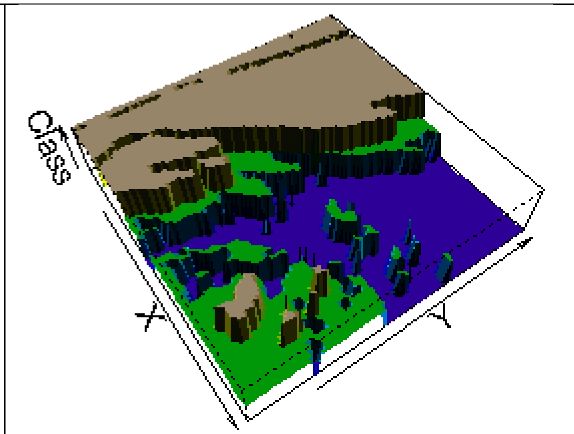
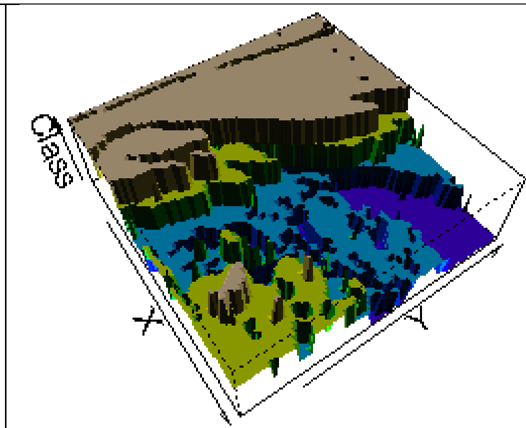
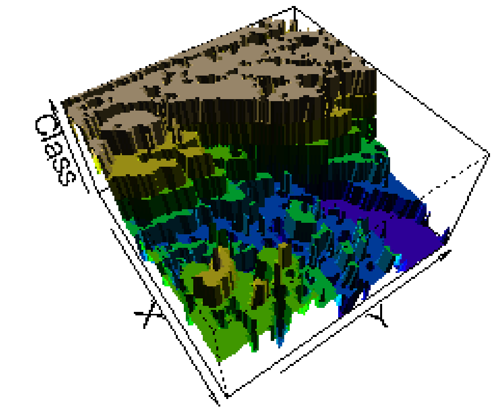
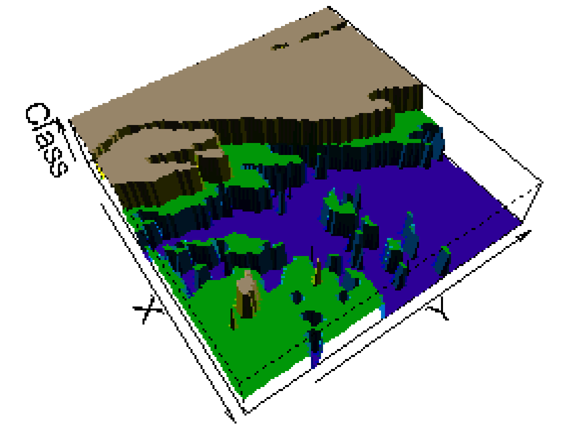
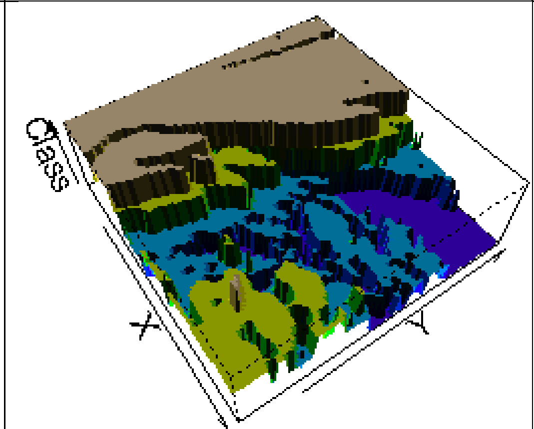
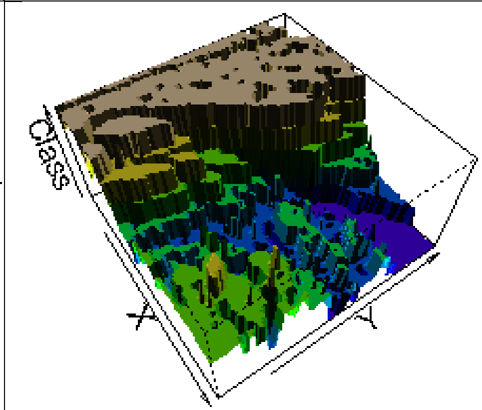
```
% %P(2,:)=XY(:,:,1,2);
% 1:10:100
net = newc([0 1;0 1],3,.1);
w = net.IW{1};
x=reshape(XY(1:10:100,1:10:100,3,1),1,[]);
y=reshape(XY(1:10:100,1:10:100,3,2),1,[]);
P=[x ;y];
plot(P(1,:),P(2,:),'+r');
hold on;
circles = plot(w(:,1),w(:,2),'ob');
net.trainParam.epochs = 6;
net = train(net,P);
w = net.IW{1};
delete(circles);
plot(w(:,1),w(:,2),'ob');
A=[];
for i=1:100
    for j=1:100
    p = [XY(i,j,3,1); XY(i,j,3,2)];
a = sim(net,p);
%b=a(1);
A(i,j)= vec2ind(a);
    end
end
%plot(,,'r+');
axes(handles.axes15);
imagesc(A);

D=B+C+A;
% A=[];
% for i=1:100
%     for j=1:100
%     if D(i,j)<3.1
%         A(i,j)=1;
%     elseif D(i,j)>3.1&&D(i,j)<6.1
%         A(i,j)=2;
%     else
%         A(i,j)=3;
%     end
%     end
% end

axes(handles.axes16);
imagesc(D); // plot of the aggregate mineral prediction colormap

fid = fopen('clda.txt','w');
fprintf(fid,'%g\n',D);
status = fclose(fid);

% fid = fopen('cldb.txt','w');
% fprintf(fid,'%g\n',B);
% status = fclose(fid);
```

```
%
% fid = fopen('cldc.txt','w');
% fprintf(fid,'%g\n',C);
% status = fclose(fid);

%plot(XY(:,:,3,1),XY(:,:,3,2),'r+');
 assignin('base', 'avgX',avgX);
  assignin('base', 'avgY',avgY);
  assignin('base', 'hX',hX);
  assignin('base', 'A',A);
%axes(handles.axes8);
%imagesc(XY(:,:,4,2));
```

<table>
<tr><td colspan="3">CLUSTER CENTRE</td></tr>
<tr><td>1</td><td>2</td><td>3</td></tr>
<tr><td>
</td><td>
</td><td>
</td></tr>
<tr><td>
</td><td>
</td><td>
</td></tr>
</table>

3D Plots of the Cluster Centre Image

	PREDICTED MINERAL MAP		
	3 classes	**4 classes**	**6 classes**
CC1			
CC2			

CC3			
Joint CC123			

3D Plots of the Predicted Mineral Maps

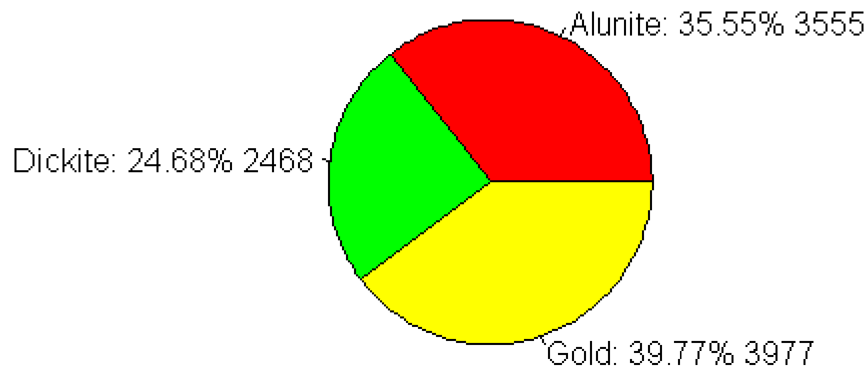
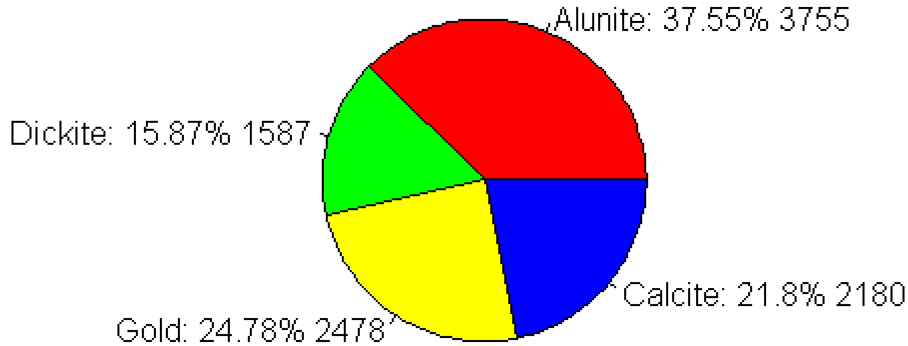


Figure 5.17: Abundance Estimate for 3 Classes



Abundance Estimate for 4 Classes

REFLECTANT DATA FROM THE SATELLITE

structure(c(-6, -15, -23, -25, -21, -23, -19, -17, -17, -17,

-23, -21, -21, -6, -10, -10, -21, -8, -26, -17, -13, -15, -23,

-13, -13, -26, -9, -17, -17, -13, -21, -13, -19, -17, -7, -2,

-4, -9, -7, 11, 13, -2, -9, 4, -2, 8, 0, -4, -2, 2, 2, -7, 2,

0, 2, -9, -11, 2, -7, -20, 4, -7, 6, -5, -7, -1, -1, -1, 6, 10,

3, -5, -3, 6, -1, -11, -7, 3, 8, 6, -3, -5, -18, -3, -10, -10,

-3, 1, -3, -10, -8, -8, -3, -5, -8, -5, 1, -16, -12, -10, -6,

-15, -23, -25, -21, -23, -19, -17, -17, -17, -23, -21, -21, -6,

-10, -10, -21, -8, -26, -17, -12, -15, -23, -12, -12, -26, -8,

-17, -17, -13, -21, -13, -19, -17, -6, -2, -4, -9, -7, 11, 13,

-2, -9, 4, -2, 8, 0, -4, -2, 2, 2, -7, 2, 0, 2, -9, -11, 2, -7,

-20, 4, -7, 6, -5, -7, 0, 0, 0, 6, 10, 4, -5, -3, 6, -1, -11,

-7, 3, 8, 6, -3, -5, -18, -3, -9, -9, -3, 1, -3, -9, -7, -7,

-3, -5, -7, -5, 1, -16, -12, -10, -6, -14, -23, -25, -21, -23,

-19, -17, -17, -17, -23, -21, -21, -6, -10, -10, -21, -8, -26,

-17, -12, -15, -23, -12, -12, -26, -8, -17, -17, -12, -21, -13,

-19, -17, -6, -2, -4, -8, -7, 11, 13, -2, -9, 4, -2, 9, 0, -4,

-2, 2, 2, -7, 2, 0, 2, -9, -11, 2, -7, -20, 4, -7, 6, -4, -7,

0, 0, 0, 6, 10, 4, -5, -3, 6, 0, -11, -7, 4, 8, 6, -3, -5, -18,

-3, -9, -9, -3, 1, -3, -9, -7, -7, -3, -5, -7, -5, 1, -16, -11,

-9, -11, -24, -6, -13, -15, -20, -22, -13, -20, -24, -5, -11,

-22, -5, -15, -15, -11, -11, -13, -20, -13, -7, -18, -24, -20,

-13, -9, -11, -12, -16, -22, -12, -14, -16, -18, 1, 6, 1, -3,

3, 14, 8, -1, 5, 12, 5, 3, 3, 5, 1, -1, -7, 7, -1, 5, -1, -5,

-12, 3, -8, 5, -6, -3, -6, -4, -6, -6, -4, 7, 5, -12, 5, 5, -10,

3, -2, 0, -21, 0, 0, -2, -10, -8, -15, -4, 0, -8, -10, 5, -6, 5, 0, -6, -10, -8, 0, -6, -8, -8, -8, -15, -23, -15, -21, -21,

-30, -13, -15, -11, -21, -6, -23, -19, -17, -21, -21, -13, -17,

-22, -11, -11, -11, -11, -20, -15, -17, -17, -17, -15, -17, -20,

-7, -11, -9, -9, -9, -5, 4, -2, 19, 4, 6, 1, 1, 2, 8, 13, 4,

-1, -5, -3, -1, 4, 1, 4, 1, -3, 1, 4, -7, -1, -7, -1, 6, 8, -1,

-1, -3, 6, -1, 6, -5, 1, -1, -7, -12, 5, -10, -7, -12, 1, -12,

-7, -14, -1, -1, -1, -1, -1, -1, -3, -10, -3, -3, -14, -3, 12,

-5, -5, -3, -9, -19, -17, -17, -28, -13, -11, -17, -15, -24,

-20, -13, -22, -22, -9, -9, -11, -24, -24, -14, -7, -16, -16,

-7, -16, -12, -12, -16, -18, -16, -22, -7, -5, -18, -7, -9, -3,

-1, -1, -5, 1, 1, -1, -3, 5, 7, 12, 5, 12, 5, 5, -8, 7, -1, 3,

-6, 7, 1, -2, -12, 9, 18, 1, -8, 9, 1, 1, 9, 3, -2, -2, -2, -2,

-4, 3, -10, -4, -6, -19, -10, 5, -2, -2, -6, 3, -6, -4, 3, 7,

-2, -2, -10, -23, -6, -26, -8, 7, -6, -10, -6, -8, -13, -15,

-25, -17, -17, -19, -19, -21, -11, -2, -15, -13, -8, -17, -17,

-6, -13, -17, -17, -19, -11, -24, -15, -19, -26, -17, -5, -13,

-24, -17, -7, -11, -3, -3, -13, -7, -5, 4, 6, 6, 4, -14, -1,

6, 6, 2, 19, 4, 6, 8, -5, 6, 6, 2, 6, 14, 3, 6, 1, 10, 12, 3,

-1, 10, 18, 18, 10, 5, -12, -5, 5, 3, 7, -3, -3, -12, -5, -12,

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