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An Intelligent System for Minerals Detection using Supervised Learning Approach

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Abstract: ***Supervised learning using ANFIS is proposed to identify classes of minerals potential in a satellite based hyperspectral data set. Spectral data for each pixel in a data set are extracted and processed to obtain a characterization map through a novel method. The characterization map is then clustered using c-means fuzzy clustering to obtain characteristic cluster center data. An ANFIS network with three membership function is trained with the cluster center data as input, and a numerical coding of the mineral map of the area as training output. The network satisfactorily learns to identify different classes of mineral and can also indicate the presence of new minerals for which it has not been trained. Such novel mineral can thus be identified and encoded for learning by the network.***

Keywords: Mineral detection, Hyperspectral data, Supervised learning, ANFIS

1. INTRODUCTION

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, it includes 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 capacitors and other products essential for modern semiconductor technology. 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.

To maintain our living standard, we must continue mining and this requires continued exploration for new deposit 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, depend 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 land. This will only be permitted if exploration can be carried out with negligible impact on the natural environment.

Modern location methods like the proposed one should be 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 we as consumers demands these products.

Mineral occur in earth crust in rare concentration known as mineral deposit.

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.

To ensure continue 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 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.

2. SCOPE OF THE WORK

The research work is restricted to the location of minerals in any part of the world where hyperspectral data is available.

An attempt is being made to use ANFIS method with wavelet transform to solve the problem of mineral location using hyperspectral data cube. Neuro-fuzzy is a combination of both Neural Network and fuzzy logic. This 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, they will be good source of income for the government, individuals, parastaters e.t.c. this will also provide better job opportunities for the citizens. In fact, it will go a long run to boost the economy of the country at large.

3. ARTIFICIAL INTELLIGENCE

Artificial intelligence is one of the youngest branches of modern science [6].

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 AI.

By definition, AI 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 [12]. AI again is defined as the science and technology which is concerned with development of computer system that is capable to think, feel, talk, hear, touch, see, perceive e.t.c.

Sugumaran [10] also defined AI as the branch of computer science that aims to create intelligent machine.

Vandal Smith [12] defined AI as the branch of computer science that is concerned with automation of intelligent behaviour. Although, most of us are certain that we know intelligence 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 evaluation of a supposedly intelligent computer program, while still capturing the validity of human mind.

Thus, the problem of defining AI becomes one of defining intelligence itself [16]. Intelligence is a capacity of a system to achieve a goal or sustain a desired behaviour under conditions of uncertainty. Intelligence systems have to cope with sources of uncertainty like occurrence of unexpected events such as unpredictable changes in the world in which the system operate and incomplete, inconsistent and unreliable information available to the system for the purpose of deciding what next [15].

Intelligent system exhibits intelligent behaviour. Intelligent behaviour, if exhibited is capable of achieving specified goals or sustaining behaviour under conditions of uncertainty even in a poor structured environment.

In this research work, an intelligent system for mineral prospecting is to be developed. AI is made up of different structures which include:

Neural Network

Expert System

Genetic Algorithm

Fuzzy Logic

3.1. NEURAL NETWORK

NN can be applied in different areas. Its important feature is its ability to recognize different pattern (pattern recognition). There is Neuron in human brain with which they learn how to identify different handwriting, differentiate dirty cloth from clean one, identify their **child in** the midst of others. Neuron in human brain **used to** identify **and/or** recognize and classify different patterns. Therefore, NN are digital representation of human brain. They are made up of artificial neuron, connected by weights which are indicative of straps of connection. The neurons are arranged inform of layers. Interaction propagation of input from one layer of neuron to the next assist the NN to learn from the past experience. His pattern recognition is based on this important feature.

Unlike human, when a Neuron is fully trained, it can classify and identify pattern in larger amount of complex data with a very high sped that will not be possible with man

According to [8], the main advantage of NN includes:

(i) They are good for modeling non-linearity and found to be very good in solving non-linear problem but it is computationally expensive

(ii) They do not require any prior knowledge of system model

(iii) They are capable of handling situations of incomplete information, compute data and they are fault tolerance

(iv) NN is fast and robust

(v) It passes learning ability and adapt to the data

(vi) NN is fast and robust

(vii) It passes learning ability and adapt to the data

3.2. EXPERT SYSTEM

Group of experts coming together to develop a system that can be used to solve real life problem using human knowledge. In the absence of an expert, such system could be used as a good replacement. At times, it may not be a complete replacement but could assist the expert to take complex decision by integrating all the knowledge it has to its knowledge base. .

ES is knowledge based system which uses the knowledge and interface procedure to solve problems that are difficult enough to be solved by human expertise. It is permanent and consistent but suffers from a knowledge bottle neck by having inability to learn or adapt to a new situation. [8]

3.3. GENETIC ALGORITHM

This class of methods is based on the mechanism of natural selection and natural genetics which combine the notion of survival of the fittest, random and yet structured search and parallel evaluation of the points in the search space [5]

Genetic algorithm accommodates all the facet of soft computing, namely uncertainty, imprecision, non-linearity and robustness [5]. GA can be used to provide a good set of initial weight for NN or can be used to fully train the NN or to find optimal network structure. It needs only rough information on the objective function and put no restriction such as differentiability and complexity on the objective function [8]. When variables are large with constraint, it requires high computational time.

3.4. FUZZY LOGIC

Logic deals with true and false. A proposition can be true on one occasion and false on another. If a proposition is true, it has a true value 1, if it false, its true value is zero. These are the only possible truth value. Propositions by means of logic operations.

When you say it will rain today you are making statement with certainty of course the statement could be true or false.

The truth values of your statements can be only 1 or 0. On the other hand, there are statements that can not be made with certainty but with certain degree of certainty. The level of certainty may be 0.7 rather 1. This is what fuzzy logic was developed to model. Fuzzy logic deals with propositions that can be true to a certain degree sometimes from 0 to 1.

Therefore, a propositions truth value indicates the degree of certainty about which the proposition is true.

In recent years, different structures of neuro-fuzzy networks have been proposed combining the advantages of neural networks and fuzzy logic [7]. Several studies using the Mamdani [4] type interference or the Takagi-Sugeno model [9]. For this study the Sugeno fuzzy model proposed by Takagi, Sugeno and Kang [9][11] had been used to generate fuzzy rules from a set of input and outputs. A typical fuzzy rule in the Sugeno fuzzy model is as follows:

If x is equal to A and y is equal to B, then z=f(x,y)

where A and B are sets of fuzzy antecedents and $z= f(x,y)$ the crisp consecutive function.

Considering the computational performance and the mathematical operations usually used (for instance, weighted sum) the Sugeno fuzzy model is the most popular inference system for fuzzy modeling based on input data [2]

4. Adaptive Neuro Fuzzy Inference System

Adaptive Neuro Fuzzy Inference System or ANFIS is a class of adaptive networks whose functionality is equivalent to a fuzzy inference system, proposed by Jang, which generates a fuzzy rule base and membership functions automatically [2].

Typically the ANFIS network topology consists of connected nodes that depend on parameters that change according to certain learning rules that minimize the error criteria. The learning technique most commonly used is the gradient method, however Jang proposed hybrid learning rule which includes the Least Square or simply LSE Estimator [2].

Considering a fuzzy system with three inputs x, y and z one output, v and a fuzzy inference Sugeno model. One possible set of rules is shown in the following equations:

Rule 1: If x is equal to A1, y is equal to B1, and z is equal to C1, then f1 = p1x + q1y + r1y + s1

Rule 2: If x is equal to A2, y is equal to B2, and z is equal to C2, then f2 = p2x + q2y + r2z + s2

As an example, illustration of the reasoning mechanism for the Sugeno inference model and the equivalent ANFIS architecture is shown in figure 1 with nodes of same layer having similar functions. Following is an explanation for each of the network layers based on Jang's excellent text [2][3].

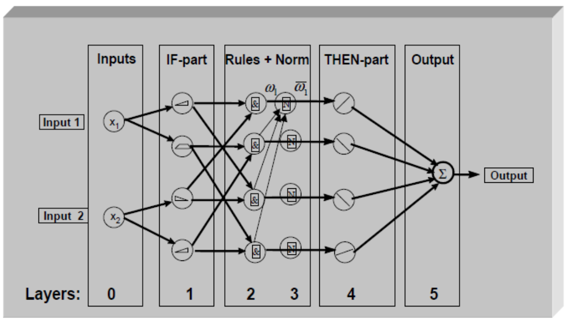


Fig 1: The general ANFIS architecture

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:

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

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

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 [14]:

Layer 1: Calculate Membership Value for Premise Parameter

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

$$o_{1,i} = \mu_{Ai}(x_1)\ for\ i = 1,2, or \quad ....3$$

$$o_{1,i} = \mu_{Bi-2}(x_2)\ for\ i = 3,4 \quad ... .4$$

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:

$$\mu_{Ai}(X_1) = \frac{1}{1 + \left|\frac{X_1 - c_i}{a_i}\right|^{2b_i}} \quad ..5$$

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:

$$o_{2,i} = w_i = \mu_{Ai}(x_1)\,\mu_{Bi}(x_2)\ for\ i = 1,2 \quad ...6$$

Layer 3: Normalize Firing Strength

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

$$o_{2,i} = \overline{W}_i = \frac{W_i}{w_1 + w_2}\quad i = 1,2 \quad ....7$$

Layer 4: Consequent Parameters

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

$$o_{4,1} = \overline{W}_i f_i = \overline{W}_i\,(p_i x_1 + q_i x_2 + r_i) \quad .... .8$$

Where w is the normalized weighting factor of the i^{th} rule, f_i is the output of the i^{th} 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:

$$Overall\ output = 0_{5,i} = \sum_i \overline{W}_i f_i = \frac{\sum_i W_i f_i}{\sum_i W_i} \quad ... .9$$

ANFIS requires a training data set of desired input/output pair (x_1, $x_2 \ldots x_m$, y) depicting the target system to be modeled. ANFIS adaptively maps the inputs (x_1, $x_2 \ldots x_m$) 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.

5. SELECTION OF INPUT DATA

Hyperspectral images can be defined as images whose pixels contain a fine sampling of the light spectra. Therefore each pixel is a high dimensional vector, whose components are the received radiance values inside a fine wavelength band of the spectra. Most of the hyperspectral sensors cover the visible light spectrum and the near infrared (NIR) spectrum. In figure 2 we show the structure of a hyperspectral image from a computational point of view. It consists of a 3D matrix, whose third dimension corresponds to the radiance spectra sampled at the pixel. The first two dimensions correspond to the spatial coordinates in the image plane. Another view of the data in a hyperspectral image is given in figure 3. In figure 4, we show an illustration of the hyperspectral image capture in a remote sensing setting. A high altitude device, either an airplane or a satellite, goes over the land picking the images. On board sensors often capture one line of the image, so that the motion of the device gives the second spatial dimension. The figure shows that different land covers produce different spectra in the corresponding image pixels. This additional spectral information has the promise of allowing image automated detection of materials highly efficient and robust without resorting to spatial processing.

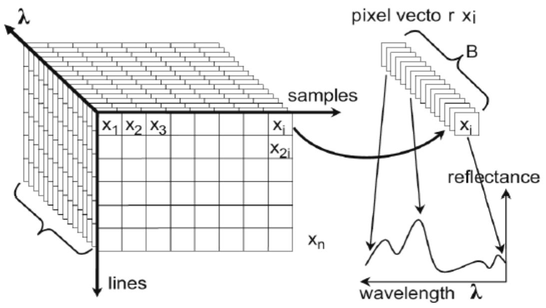


Figure 2: Structure of a hyperspectral image

6. DATA

The test data consists of specter data for Cuprite, Nevada. The data consists of 600 by 320 pixels with 357 band spectrum ranging from 0.4 µm to 2.5 µm. Fig 3 shows the hyperspectral data cube while Fig 4 shows a colormap slice (a band) of the given data. Fig 5 shows the 3D plots of some band data.

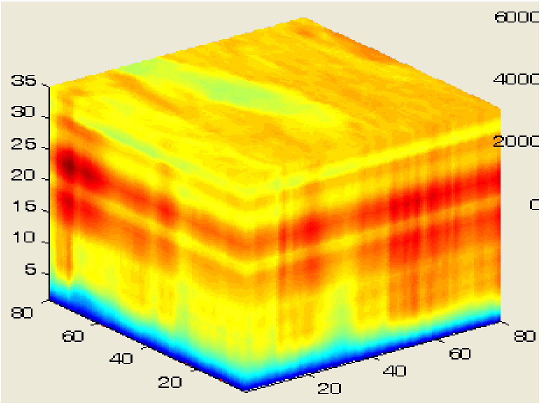


Fig 3: Data cube image of hyperspectral data

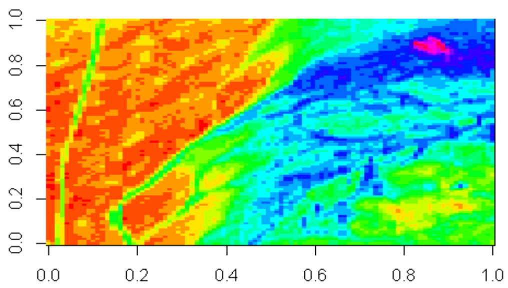
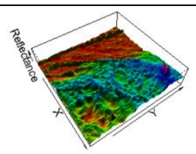
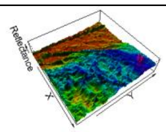


Fig 4: A band (slice) of hyperspectral data

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

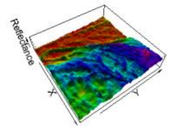
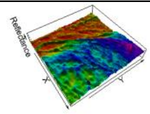
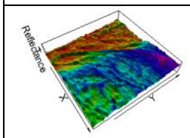
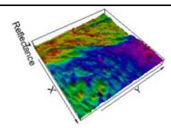
	
Band 250	Band 300
	

Figure 5: 3D Plot of some bands of the input data

7. PROCESSING OF SPECTRUM FOR EACH PIXEL.

The spectrum for each pixel is selected in turn, displayed in figure 6 and turned into charaterisation map as explained in the design and implementation. The characterization map for a particular pixel is shown in figure 7. The characterization map is then clustered to obtain 3 cluster centers marked in red in figure 7. The cluster center data for each pixel is thus calculated in turn and stored in a cluster center data structure for file storage or further processing. The cluster center data distill the essential features for classification and recognition of mineral classes in the given data. Figure 8 shows the 3D plots of the cluster center data.

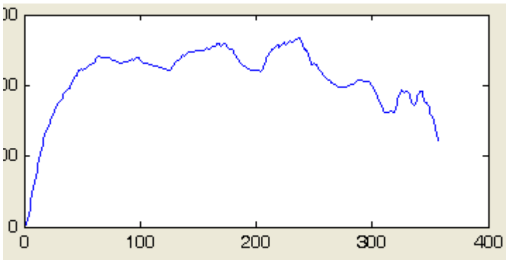


Figure 6: The spectrum of a pixel

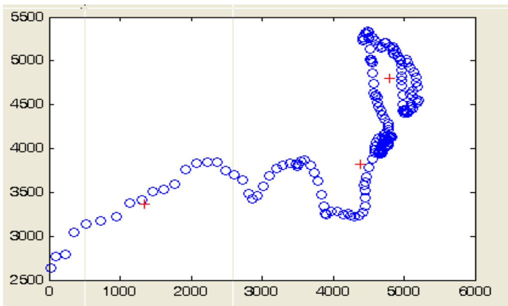


Figure 7: Clustered image of a pixel with 3 cluster centers shown in red

Figure 8: 3D Plots of the cluster center data

8. SUPERVISED LEARNING WITH ANFIS

Furthermore, I wish to create a system that learns to recognize classes of mineral with time as discussed under the design and implementation section. I carried out the test of this methodology by using a sugeno-type ANFIS network to learn to classify minerals overtime. The ANFIS network consists of six input node and one output node. The cluster center coordinate data are used as input with the aggregate value from the kohonen network classification used as output. The scheme of the network is shown in Fig 9. The initial training data set is shown in Fig 10. The question arises as to optimum choice of the number of membership functions required. I wish to minimize the number of membership functions so as to reduce the size of our network. But initial test runs shows that two membership functions does not suffice as the network did not converge and mixes most of the targets during test as shown in the comparison Fig11. Therefore I have to use three membership functions and henceforth I shall discuss the results for the network with three membership functions.

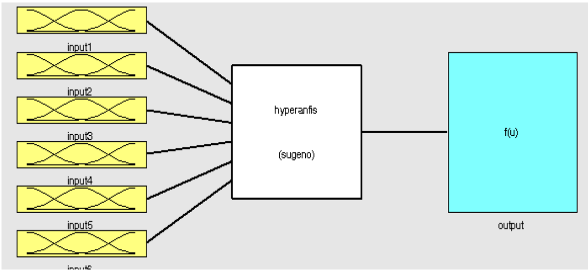


Fig 9: Scheme of the ANFIS network

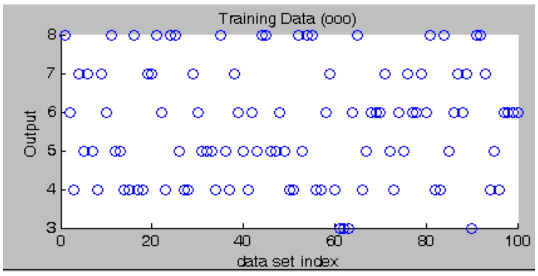
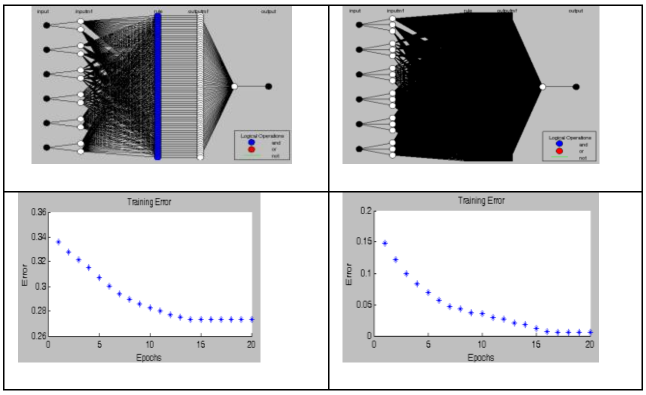
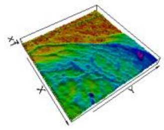
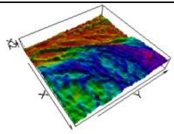
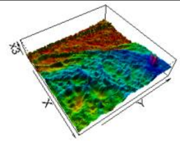
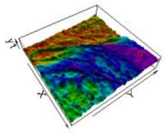
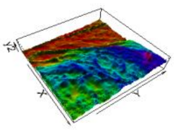
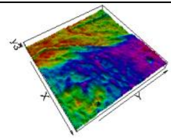


Fig 10: Training data set for ANFIS network



	CLUSTER CENTER		
	1	2	3
X			
Y			

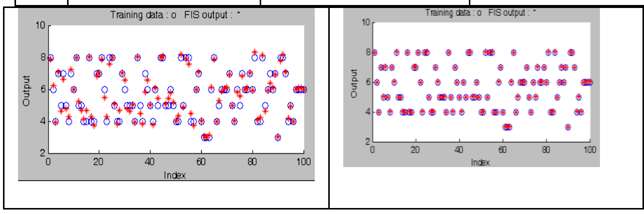


Fig 11: Comparison of performance of ANFIS network with 2 or 3 membership functions

With three membership function, the network learnt to classify the samples with approximately zero error level within 20 epochs as shown in Fig. Test with original training sample shows a 100% score as shown by all the red marks inside blue in Fig 11.

9. NOVEL MINERAL

In Fig 11, 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 needs 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 Fig 12 or as rule surfaces that shows how inputs combine with one another as shown in Fig 13. Also the shape of the membership functions change as the system learns as depicted in Fig 14.

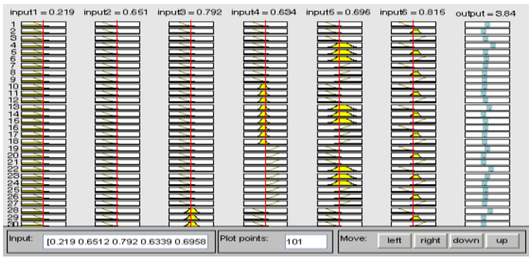


Fig 12: Rule base of the trained network

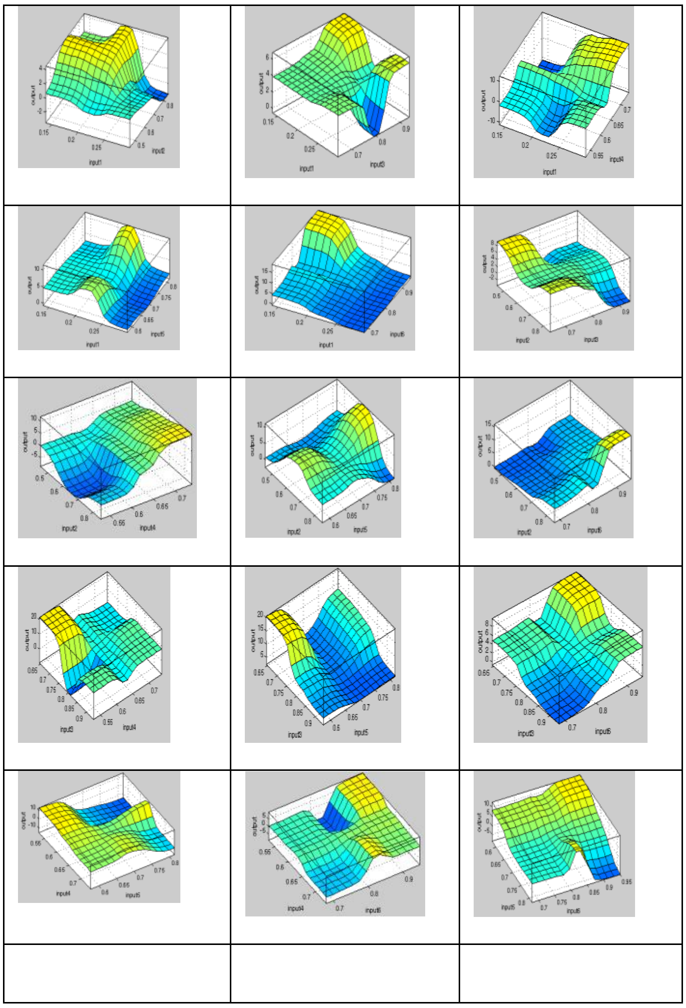


Fig 13: Rule surfaces of the trained network

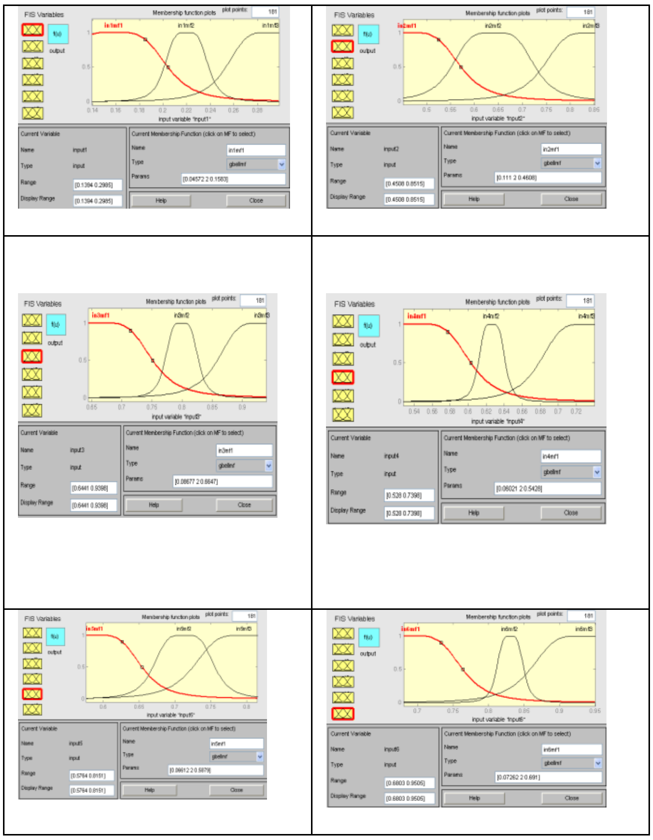


Fig 14: Membership functions of the trained network

10. 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, i proceed as follows: the class of mineral represented by each pixel 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 pixels in the given area multiplied by the given area. This algorithm will work even in case of volume data as the number of pixel in given volume data is proportional to the volume of the sought mineral.

Reserve estimate = No. of pixel in a class / Total no. of pixel X area

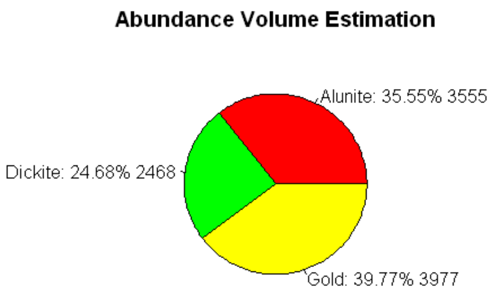


Fig 15: Abundance estimate for 3 classes

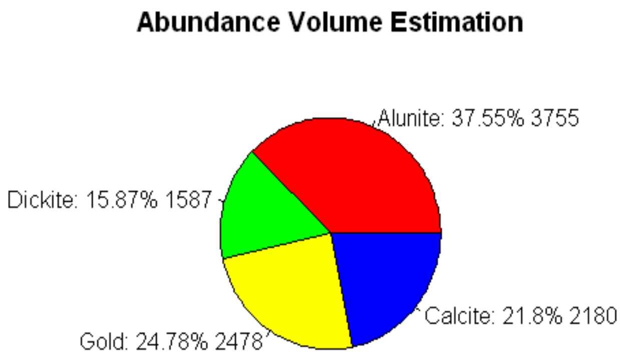


Fig 16: Abundance estimate for 4 classes

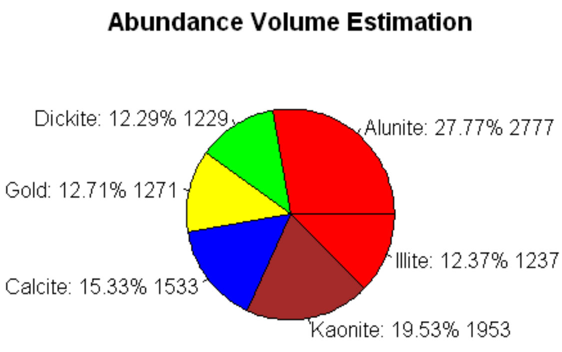


Fig 17: Abundance estimate for 6 classes

11. CONCLUSION

An intelligent system for mineral prospecting is developed using ANFIS. Hyperspectral data was collected from the satellite. Characterization map was obtained. The characterization map was clustered using c-means fuzzy clustering to obtain characteristic cluster center. An ANFIS network with 3 membership function is trained with the cluster center data as input and numerical coding of mineral map of the area as training output.

Eventually, six (6) classes of minerals were identified and named. Novel mineral is also detected. The relative percentage (%) of each of them was also estimated.

The research will be a useful tool in mining and related industries.

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