Designing a Software for Classifying Objects for Air Photos & Satellite Images using Soft Computing

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in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Computer Science

By

Samaher Hussein Ali Al-Janabi

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بسم الله الرحمن الرحيم

وعلمك ما لم تكن تعلم وكان فضل الله عليك عظيما"

صدق الله العظيم

(سورة النساء113)

Supervisor Certification

We certify that this thesis was prepared under our supervision at the Department of Computer Science/College of Science/Babylon University , by **Samaher Hussein Ali** as partial fulfillment of the requirements for the degree of Master of Science in Computer Science.

Signature: N. H. Kaghed

Name: **Dr. Nabeel Hashem Kaghad**

Title: **Professor**

Date: 31 /10/2005

Signature:

Name: **Dr. Tawfiq A. Abbas**

Title: **Assistant Professor**

Date: 31/10/2005

In view of the available recommendations, I forward this thesis for debate by the examination committee.

Signature:

Name: **Dr. Abbas Mohson Al-Bakry**

Title: **Head of the department of Computer Science, Babylon University**

Date: 31/10/2005

Certification of the Examination Committee

We chairman and members of the examination committee, certify that we have studied the thesis in titled **(Designing a Software for Classifying Objects for Air Photos & Satellite Images using Soft Computing)** presented by the student **Samaher Hussein Ali** and examined her in its contents and in what is related to it, and we have found it worthy to be accepted for the degree of **Master of Science in Computer Science** with **Excellent Degree.**

Signature: S. B. Sadkhan
Name: **Dr. Sattar Bader Sadkhan**
Title: **Professor**
Date: / /**2005**
(Chairman)

Signature:
Name: **Dr. Abd Al-Hassan Khilawi**
Title: **Assistant Professor**
Date: 20 /12 /**2005**
(Member)

Signature:
Name: **Dr. Abbas Mohson Al-Bakry**
Title: **Lecture**
Date: 19 /12 /**2005**
(Member)

Signature: N. H. Kaghad
Name: **Dr. Nabeel Hashem Kaghad**
Title: **Professor**
Date: 19 /12/**2005**
(Supervisor)

Signature:
Name: **Dr. Tawfiq A. Abbas**
Title: **Assistant Professor**
Date: 9 /12/**2005**
(Supervisor)

Signature:
Name: **Dr. Oda M.Y. Al-Zamely**
Title: **Dean of College of Science in Babylon University**
Date: / /2005

الإهداء

إلى سر وجودي ونور عيوني ...والدي الحبيب

إلى بحر الحنان وينبوع الأمل...والدتي الحبيبة

إلى الشموع الذين بوجودهم تكتمل سعادتي أخوتي الأعزاء

(أيهاب...علي ... أمير)

إلى النجمة التي أنارت حياتي أختي الغالية ... نورا

والى كل من أطعمني أدباً وسقاني علماً في هذه الحياة

اهدي جهدي المتواضع هذا

سماهر

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Abstract

This research presents a method to design programming system using hybrid techniques represented soft computing to classify objects from the air photos and satellite images depending on their features with minimum acceptable error.

These images usually consist of seven layers, while the work in this research focuses on dealing with three bands (red ,green and blue). This search concerns with classifying five kinds of objects (urban area, forests, roads, rivers, football-stadiums).

Accordingly, The database which describes that objects by depending on their attributes were built .

Then, the Evolution algorithm of type breeder genetic algorithm to procedure genetic clustering process to segment image which provides a number of clusters found in that image data set were used . To avoid the overlapping between clusters with other, one of the clustering validity measures called "Davies-Bouldin index" as fitness function of that algorithm was used. Moreover, four methods of the recombination in it (Discrete Recombination, Extended Line Recombination, Extended Intermediate Recombination, Fuzzy Recombination)were discussed .

Then, two types of features for each cluster which are visual features including (Pattern, Shape, Texture, Shadow, Associative), and statistical features represented by spectrum features that include (Intensity ,Hue, Saturation) were extracted.

After that, feed forward neural network from type error back propagation neural network to determine the class under which each feature vector belongs to was used.

At the last stage, IF-Then rule to form several rules that govern each class attributes were used .

List of Symbols

Symbol	Meaning
ANN	Artificial Neural Network
BPNN	Back Propagation Neural Network
BN	Bayesian Networks
BMP	Bit Map Picture
BGA	Breeder Genetic Algorithm
CM	Continuous Mutation
CNN	Cumulative Neural Network
DBI	Davies-Bouldin Index
DIP	Digital Image Processing
DM	Discrete Mutation
DR	Discrete Recombination
EM	Electromagnetic
EP	Evolutionary Programming
ES	Evolution Strategies
EA	Evolutionary Algorithms
EIR	Extended Intermediate Recombination
ELR	Extended Line Recombination
FBNN	Feed Back Neural Network
FFNN	Feed Forward Neural Network
FA	Fuzzy Arithmetic
FGT	Fuzzy Graph Theory
FL	Fuzzy Logic
FR	Fuzzy Recombination
GA	Genetic Algorithm
HSI	Hue-Saturation–Intensity space
IR	Infrared
MRE	Mean Relative Error
MSE	Mean-Square Error
PDP	Parallel Distributed Processing
RGB	Red-Green-Blue images
RS	Remote Sensing
SC	Soft Computing

List of Abbreviation

Symbol	Meaning
d	Constant related by BGA
S_i	Input vectors
η	Learning factor
δ_k	Error signal value of hidden layers
δ_j	Error signal value of output layer
O_j	Actual output value
d_j	Desired output value
P	Number of patterns
Δw_{kj}	Changing weight between hidden and output layers
Δv_{ik}	Changing weight between input and hidden layers
E_{max}	Maximum error enable of network
$E_{pochmax}$	Maximum number of epochs
h_k	Output of hidden layers
θ_j	Bais neuron
λ	Constant value equal 1
$\bar{F}(net)$	Derivative of sigmoid Function

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Chapter One

Introduction

1-1 General Introduction

Most of computations - manual or computerized - are performed in the traditional hard computing way, where the primary selection are precision, certainty and determinity. Precision, in this context, is merely a matter of digits to represent a number rather than an attribute of certainty, or how well a parameter is defined [1].

Down to the lowest level, all hard computing tasks can be decomposed into logical rules and elementary operations where the result is always the same if the same operations are performed. As computers are creations of men, hard computing naturally originates from the way human beings can analyse information. But human beings can do more than drawing conclusions obeying some logical rules and this is why the idea of intelligent computers and machines have fascinated many researchers and thinkers over decades and centuries. Hence, attempts are made to model, understand and even define the human intelligence and to transfer some features of it to manmade machines.

On the other hand traditional hard computing, the prime selection are precision, certainty, and rigor. By contrast, in soft computing the principal notion is that precision and certainty carry cost and that computation, reasoning, and decision-making should exploit(wherever possible) the tolerance for imprecision, uncertainty, approximate reasoning, and partial truth for obtaining low-cost solutions. This leads to the remarkable human ability of understanding distorted speech, deciphering sloppy hand writing, comprehending the nuances of natural language, summarizing text, recognizing and classifying images, driving a vehicle in dense traffic and, more generally, making rational decisions in an environment of uncertainty and imprecision[2].

As a result to solve any problems in the real life, a suitable problem solve techniques should be selected. where these techniques can be divide into two types and
Figure (1-1) explains the problem solving Technologics [3].

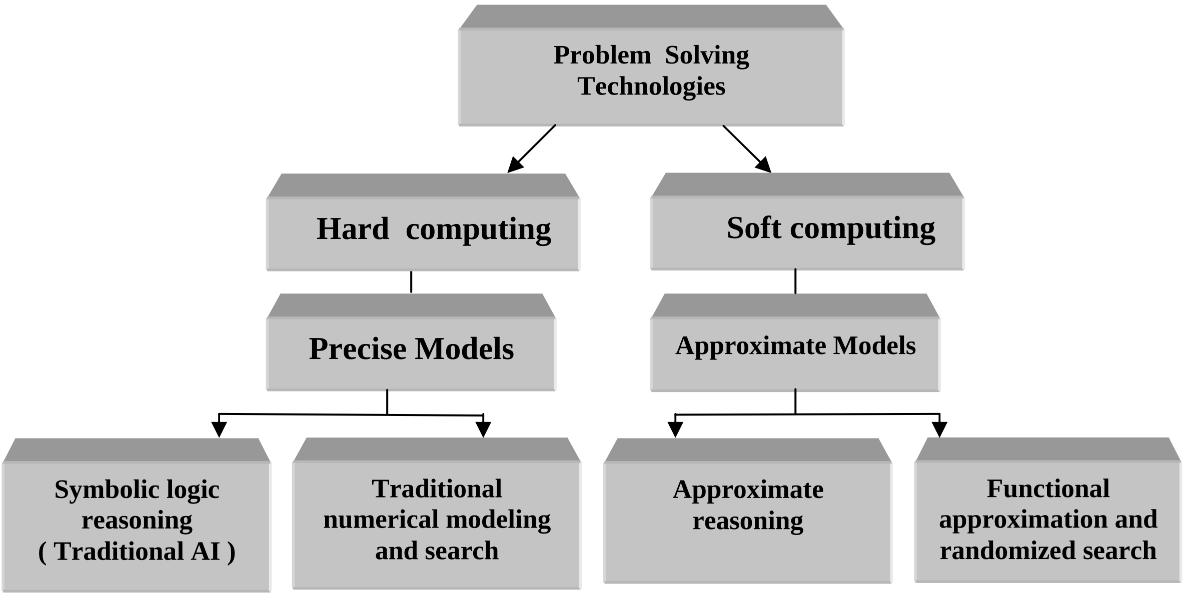


Figure (1-1): Problem Solving Technologics

Therefore Soft computing is an umbrella term for a collection of computing techniques. The term was first coined by Professor Lotfi Zadeh, who developed the concept of fuzzy logic in the mid 60's. In his words:

"Soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty and partial truth. In effect, the role model for soft computing is the human mind. The guiding principle of soft computing is: Exploit the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost" [4].

And the term Soft Computing(SC) refers to a family of computing techniques that originally comprise five different partners: fuzzy logic, evolutionary computation, neural networks , probabilistic reasoning and hybrid system. The term SC distinguishes these techniques from hard computing which is considered less flexible and computationally demanding. The key point of the transition from hard computing to SC is the observation that the computational effort required by conventional computing techniques sometimes not only makes a problem intractable, but is also unnecessary as in many applications precision can be sacrificed in order to accomplish more economical, less complex and more feasible solutions[5].

The studies explain that SC means the same as computational Intelligence, and not surprisingly the terms are used concurrently where both terms are also used to proof distinct concepts in the five fields above (artificial neural networks, fuzzy set theory and evolutionary computing, probabilistic reasoning, hybrid system) each of which can be further divided into subclasses, for example fuzzy set theory can be divided into fuzzy logic, fuzzy arithmetic and fuzzy graph theory. Evolutionary computing in turn contributes to them at least by genetic algorithms, evolutionary programming, evolution strategies and artificial life .These approaches are explaining in Figure (1-2).

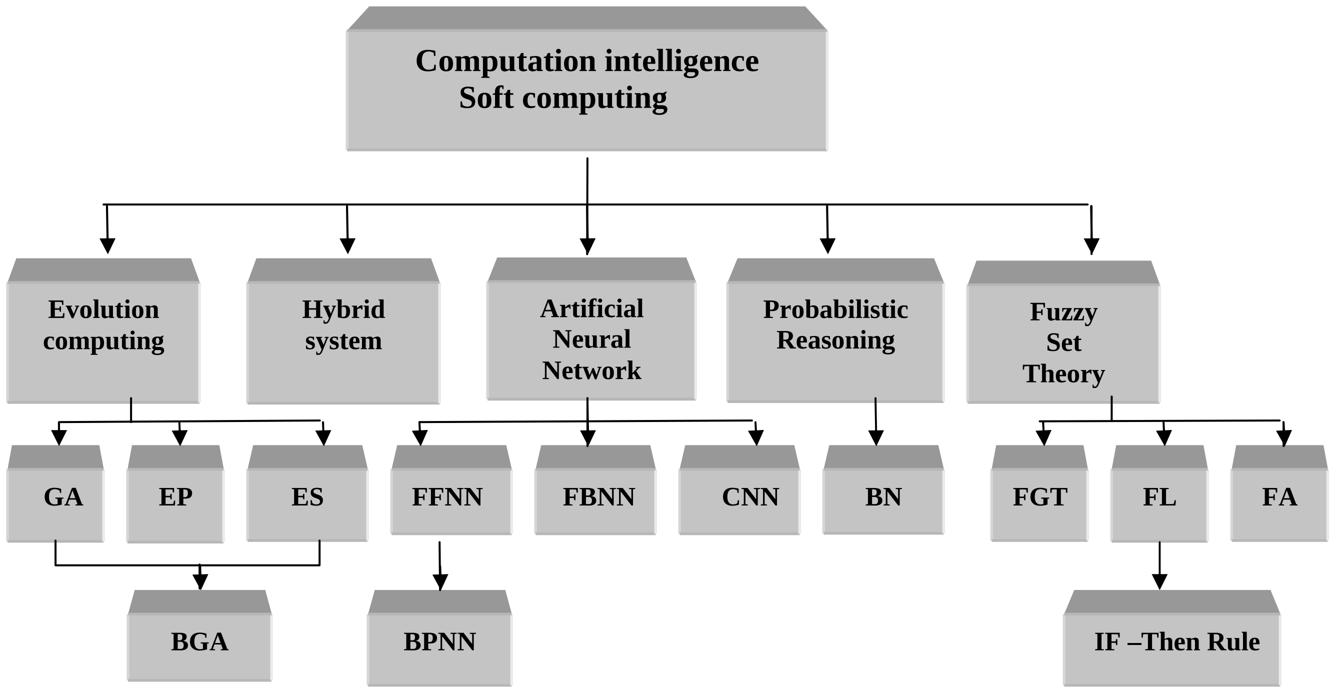


Figure (1-2): Approaches for Soft Computing

1-2 General Concepts to the Main Tasks of the problem

1-2-1 Digital Image Processing(DIP):-

DIP is one of the important fields in computer science that is concerned with the computer processing of images. These images come from many sources such as digital cameras, scanners, and satellite sensors, and are stored as a file of specific format. In general, the purpose of digital image processing is to enhance or improve the image in some way, or to extract information from it [6]. Typical operations are to :-

- Remove the blur from an image .
- Smooth out the graininess, speckle, or noise in image.
- Segment an image into regions such as objects and background.
- Remove distortion from an image.
- Improve the contrast or other visual properties of an image prior to displaying it.
- Magnify, minimize or rotate an image .
- Code the image into some efficient way for storage or transmission.

1-2-2 Remote Sensing(RS):-

RS simply refers to the science of acquiring information about some property of an object through the use of measuring device ,which is not in physical contact with the object under investigation. This science's name is coined by the United State Office of Naval Research in 1960.

RS has taken discipline dependent meaning in the environmental sciences of geography, geology, botany, zoology, foresty, meterology, agriculture, oceanography and civil engineering. It usually refers to the use of electromagnetic radiation sensory to record images of the environment which can be interpreted to yield useful information.

RS sensors and techniques improve our capability to gather information about the earth's natural resources and environment. We need this improved capability in several cases[7] :

- To improve our ability to invent and hence manage the earth's dwindling natural resources.
- To monitor changes in our deteriorating environment.
- To avoid the politically and economically ill- advised international trade of natural resources.

1-2-3 Evolutionary Algorithms(EA):-

The term EA refers to a big family of search methods based on concepts taken from Darwinian evolution of species and natural selection of the fittest [8]. Moreover, EA uses the Darwinian principle of "survival of the fittest" to evolve optimum solutions to problems[4]. Additionally, it maintains a population of individuals that represent potential solutions to it.

The three main representatives of EAs are[4][8]:-

- Genetic Algorithms (GAs) proposed by Holland 1975.
- Evolution strategies (ES) developed by Rechenberg and Schwefel during 60's and more or less settled in 70's.
- Evolutionary Programming(EP) introduced by Fogel.

1-2-4 Artificial Neural Networks(ANN):-

An Artificial neural network is an information-processing system that has certain performance characteristics in common with biological neural networks. Artificial neural networks have been developed as generalizations of mathematical models of human cognition or neural biology based on the assumptions that:

- Information processing occurs at many simple elements called neurons.
- Signals are passed between neurons over connection links.
- Each connection link has an associated weight which, in a typical neural net, multiplies the signal transmitted.
- Each neuron applies an activation function (usually nonlinear)to its net input (sum of weighted input signals)to determine its output signals[9].

1-2-5 Breeder Genetic Algorithm(BGA):-

BGA represents a class of random optimization techniques gleaned from the science of population genetics, which have proved their ability to solve hard optimization problems with continuous parameters. BGA which can be seen as a recombination between Evoluation strategies (ES)and Genetic Algorithm(GA), uses truncation selection which is very similar to the (u ,λ)strategy in ESs which will explaining in chapter two paragraph(2-4) and the search process is mainly driven by recombination making BGAs very similar to GAs. It has been proven that BGAs can solve problems more efficiently than GAs due to the theoretical faster convergence to the optimum and they can, like GAs, be easily written in a parallel form[10].

1-3 Literatures Survey

Peddle, 1993[11] stated a procedure for analyzing modern and future remote sensing data sets to address the methodological limitations of conventional approaches to image processing and classification. He provided different scales of measurement factors that confound the use of conventional Maximum Likelihood (ML)and Linear Discriminate Analysis(LDA) Algorithms. Twelve different combinations of variables selected from a multi-source data set of Spot Satellite imagery, image texture, and geomorgpometric variables from a digital elevation model were submitted to each classifier and the overall classification accuracies were compared. Maximum Likelihood classification accuracy peaked using four variables and decreased as additional variables were added.

Linear Discriminate Analysis and Evidential Reasoning showed the opposite trend of the three classifier, only Evidential Reasoning could process aspect measures directly while an incidence transformation was required for both ML and LDA. Evidential Reasoning classification accuracy was higher when aspect was used instead of incidence, suggesting information loss due to data transformations.

Peterson, 1997[12] evaluated the effectiveness of digital image analysis in the production of land cover maps. He applied unsupervised and supervised classifications using 1993 Spot satellite imagery of Boca Raton, Florida . He used three bands, including the green, red and infrared bands. The unsupervised classification which was based on the filtered data produced the best homogeneous classified areas.
The reclassified image based on the textural supervised classification is the most useful final map in the context of the study. The purpose of this study is to generate a limited category land cover map of the Greater Boca Raton area. This study evaluates the effectiveness of digital image analysis in the production of land cover maps. The five broad land cover classes used are, as follows:
(Commercial, Residential, Agricultural, Vacant and water). The project includes the generation of the following:

- false color composites:
  generate false color composite(COMPOSIT)
- unsupervised classification :
  cluster(CLUSTER)
- supervised classification:
  parellelepiped(PIPED)
  maximum likelihood(MAXLIKE)

Schaale, 2000[13] presents standard techniques for the analysis of remote sensing imager data making use of the multispectral information only. These techniques are based on the inherent statistitics of the scene under investigation and they usually neglect the neighborhood of an analysed pixel, that is the context information. Thus, standerd algorithms like vector quantization algorithms or the
Maximum Likelihood classifier do not make use of the context information inherently contained in the image data. For this reason, a valuable part of the gathered information

is not used by the data analysis. The main reason for this standard approach is that it is still a challenging task to extract textural information from image data by a reliable and robust feature extraction scheme. By using image data rescaled to a standard flight height and by using physiological findings in the visual cortex we developed a scheme for the extraction of textural information based on Gabor wavelets being invariant with respect to illumination and rotation. A supervised feed forward neural network then approximates the functional relationship between the high–dimensional feature data space and the predefined texture classes.

Nikola, et al 2001[14] present a methodology for image classification of both spatial and spectral data with the use of hybrid evolving fuzzy neural networks (EFuNNS). EFuNNs are five layer sparsely connected networks. EFuNNs contain dynamic structures that evolve by growing and pruning of neurons and connections. EFuNNS merge three supervised classification methods: connectionism, fuzzy logic, and case-based reasoning. By merging these strategies, the structure become capable of learning and generalising from a small sample set of large attribute vectors as well as from large sample sets and small feature vectors. Two case studies were discussed in this methodology. First, related to an environmental remote sensing application, and second, large scale images of fruit for automated grading.

The proposed methodology provides fast and accurate adaptive learning for image classification. A System Pour l'Observation de la Terre (SPOT) satellite image of the Otago Harbour, Dunedin, New Zealand, was used for the classification. The SPOT image has 3 spectral bands sensing the green, red and infrared portions of the electromagnetic spectrum. Ten cover types, containing intertidal vegetation and substrates, were recorded during a ground reference survey and classification .

Sanghamitra and Ujjwall, 2002[15] submit a method depending on the Genetic clustering technique to classify satellite image of a part of the city Calcatta. The image is in the multispectral mode having two bands :red and near infrared , the aim of this method is to classify the image (in two bands)by using unsupervised classification (clustering) and this method is also able to automatically identify several land cover types depending on prior knowledge about the city .

Leena and Jorma, 2003[16] present a classification method of the texture samples which was based on the k-nearest neighbor method. In this method a rock texture classification depended on textural and spectral features of the rock, where the spectral features were considered as some color parameters while the textural features were calculated from the co-occurrence matrix. In this classification method, non-homogenous texture images are divided into blocks and the feature values are calculated for each block separately. This classification method was tested by using two types of rock textures (homogenous and non-homogenous).

1-4 Thesis Objectives

The objective of thesis is present method to design programming system using hybrid techniques represented by soft computing to classify objects from Remote Sensing Imageries(i.e., air photos and/or a satellite images) depending on their features with minimum acceptable error. This search concerns with classifying five kinds of objects (urban area, forests, roads, rivers, football-stadiums).

1-5 Contribution of the Thesis

The major contribution of this thesis can be summarized as follows:-

First, building visual description for each object in the image and then using this description with spectrum features as image database .

Second, investigating one of the new optimization technique called breeder genetic algorithm to clustering image without a known number of clusters and using the histogram as a measure to determine the length of chromosome in the population (i.e., dynamic length of the chromosome is used) by taking fixed percentage from higher peaks in histogram and validity from clustering by using Davies-Bouldin index .

Third, two types of features (mathematical and description) are extracted from each cluster.

Fourth, using these features to train neural network and determine the class for each feature vector .

Fifth, forming several rules that govern each class attributes (i.e., verification from correct decisions)by using the IF-Then Rule.

The project in this thesis includes the generation of the following:-

- true color composites:
  generate true color composite(Red,Green,Blue)
- visual description
  building database(DATABASE)
- unsupervised classification :
  breeder unknown number of cluster genetic algorithm (CLUSTER)
- supervised classification:
  Back Propagation Neural Network(BPNN)
- forming rules
  IF-Then Rule

1-6 Thesis Layout

- Chapter two: focuses on the theoretical concepts related to this work: digital image classification, remote sensing, segmentation, evolutionary algorithm, breeder genetic algorithm and back propagation neural network.
- Chapter three: explain the proposed system used in classifying objects for Air Photos and Satellite Images. Each step in the proposed system has been explained and analyzed extensively .
- Chapter four: illustrates the implementation of proposed system and the results of the cases study.
- Chapter five: show conclusions of this work together with some recommendations for future work in this field.

Chapter Two

Basic Concepts about the Research Subject

2-1 Introduction

A broad group of digital image processing techniques is directed toward image classification, the automated grouping of all or selected land cover features into summary categories. Image classification techniques are most generally applied to the spectral data of the signal data image, or to the varying spectral data of a series of multi-data images.

The objective of image classification is: giving a set of objects, assigning each object to one of a set classes. For the study purposes, the objects are the pixels in the image and classes are the various categories occurring in the image.

Classified maps derived from remotely sensed data are important in numerous ways. The validity of the data as a basis for scientific research is dependent on map accuracy. However, accuracy assessment techniques have not yet been perfect and are also subject to error. The most obvious source of error is the assumption that the standard or reference map to which the classified image is compared is accurate. The standard may have inaccuracies derived by the same sources of error.

The classification process can be described as a form of pattern recognition or identification of the pattern associated with each pixel position in an image in terms of the characteristics of objects or materials at the corresponding point on the Earth's surface.

Pattern recognition needs knowledge about the object. Image features that capture the essential traits of an object and are insensitive to different procedural changes are ideal for recognition.

Pattern classification is usually achieved by following a two-stage process. First a suitable set of features with the desired invariance properties is extracted from the patterns selected for classification; this step is then followed by a presentation of the extracted features to classifier whose purpose is to partition the space of features into decision regions corresponding to each pattern class [17]. The selection of appropriate features is the key to solve the problem. The success of any such practical system depends critically upon how far a set of appropriate numerical attributes or features can be extracted from the object of interest for purpose of classification.

2-2 Remote Sensing

"Remote sensing is the science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information" [18].

2-2-1 Elements of Remote Sensing System

In much of remote sensing, the process involves an interaction between incident radiation and the targets of interest. This is exemplified by the use of imaging systems where the following seven elements are involved, as illustrated in Figure(2-1). Note, however that remote sensing also involves the sensing of emitted energy and the use of non-imaging sensors[18].

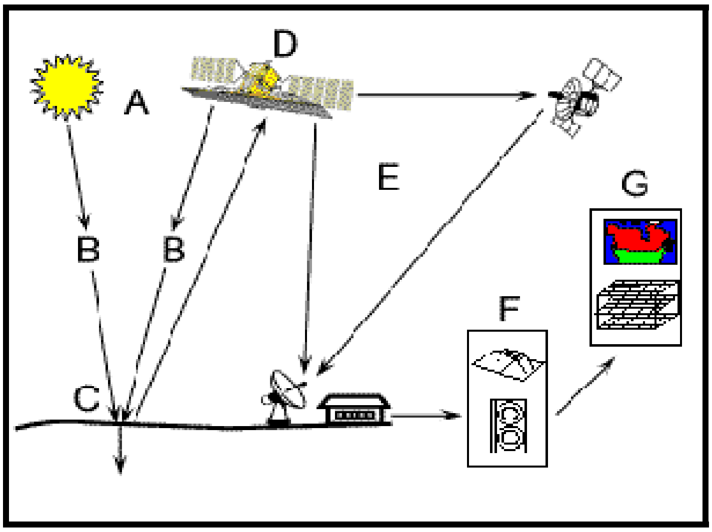


Figure (2-1): Element of remote sensing system

The following seven elements comprise the remote sensing process from the beginning to the end:-

1- Energy Source or Illumination (A):- the first requirement for remote sensing is to have an energy source which illuminates or provides electromagnetic energy to the target of interest.
2- Radiation and the Atmosphere (B):- as the energy travels from its source to the target, it will come in contact and interact with the atmosphere it passes through. This interaction may take place a second time as the energy travels from the target to the sensor.
3- Interaction with the Target (C):- once the energy makes its way to the target through the atmosphere, it interacts with the target depending on the properties of both the target and the radiation.
4- Recording of Energy by the Sensor (D) :- after the energy has been scattered by, or emitted from the target, we require a sensor (remote - not in contact with the target) to collect and record the electromagnetic radiation.
5- Transmission, Reception, and Processing (E) **:-** the energy recorded by the sensor has to be transmitted, often in electronic form, to a receiving and processing station where the data are processed into an image (hardcopy and/or digital).
6- Interpretation and Analysis (F) :- the processed image is interpreted, visually and/or digitally or electronically, to extract information about the target which was illuminated.
7- Application (G) :- the final element of the remote sensing process is achieved when we apply the information we have been able to extract from the imagery about the target in order to better understand it, reveal some new information, or assist in solving a particular problem.

2-2-2 The Electromagnetic Spectrum

Electromagnetic energy is the link between the components(source of illumination, target and sensor)of the remote sensing system. According to Maxwell s formulation, electromagnetic radiation is a dynamic form of energy which makes itself manifest only through the interaction with matter. While the modern electromagnetic radiation theory defines it as the continuum of energy that ranges from less than nanometers to meters in wavelength, travels at the speed of light, and propagates through a vacuum. Figure (2-2b)illustrates the electromagnetic spectrum regions.[7]

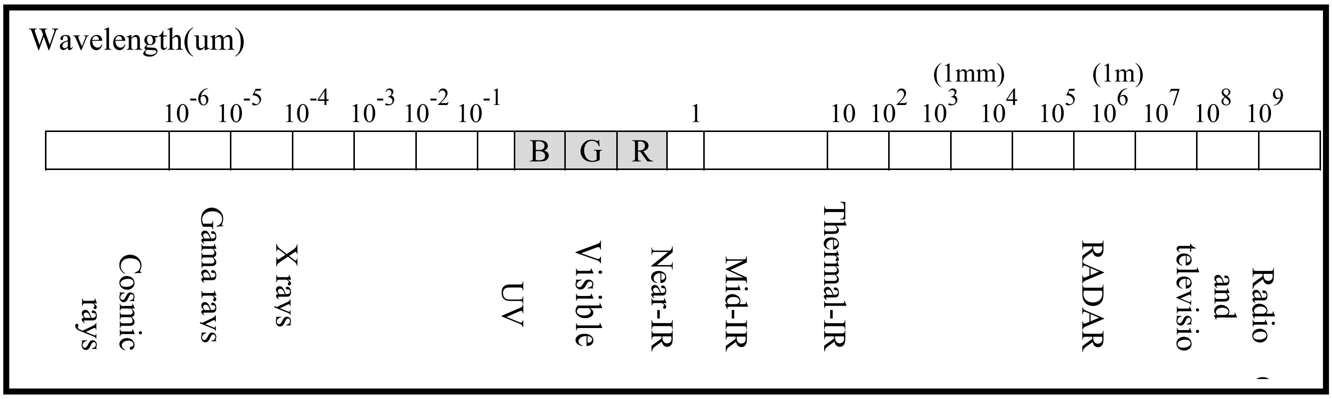


Figure (2-2a): The Electromagnetic Spectrum

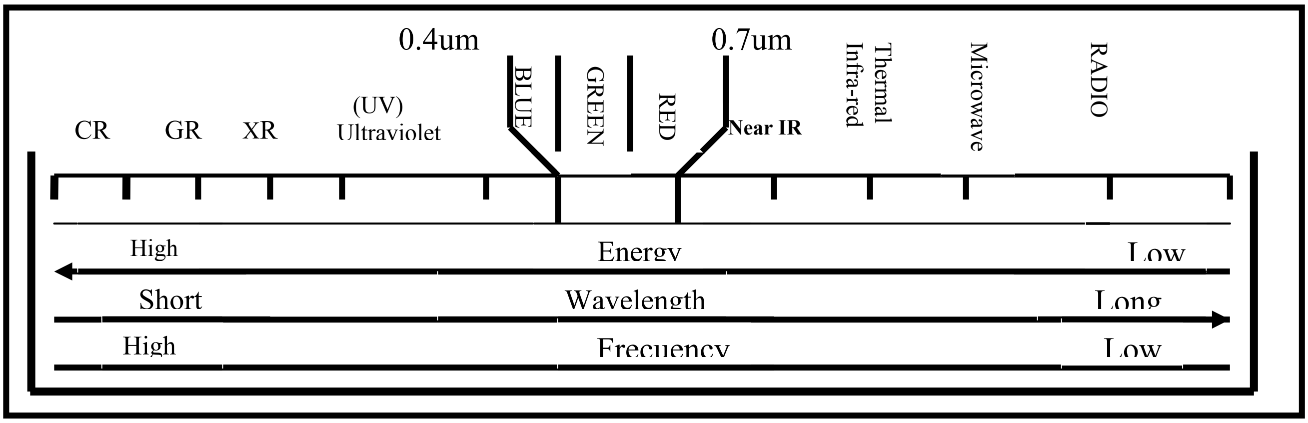


Figure (2-2b): The Electromagnetic Spectrum regions

Three measurements are used to describe electromagnetic energy, these are wavelength(λ)in micrometers(μm), which is the distance between successive wave peaks frequency(f)in hertz(Hz), which is the number of wave peaks passing a fixed point in space per unit time, and velocity(c) in ($m.sec^{-1}$)which within a given medium is constant at the speed of light. The relationship of these measurements, is

$$\lambda=c/f \qquad \text{…………………(2-1)}$$

Several regions of the electromagnetic spectrum are of particular interest for remote sensing, those of most importance being the visible, infrared, and microwave regions.

Visible region in the EM spectrum ranges from 0.4 μm to 0.7 μm .The significance of this region stems from the fact that the radiation emitted from the sun reaches a peak value within this region at 0.48 μm .

IR region is represented by spectral band, which lies between the visible and microwave region. The IR band is commonly further subdivided into four bands. They include the reflected infrared (3-7 μm), the middle infrared (3-6 μm),the far infrared (6-15 μm) and the extreme infrared(15-1000 μm).

The microwave region of electromagnetic spectrum ranges from 1 mm(10^3 μm)to 1m(10^6 μm).

In this work we deal with the visible region in the EM spectrum only and the following figure (2-3)shows the visible spectrum(red ,green, blue)bands.

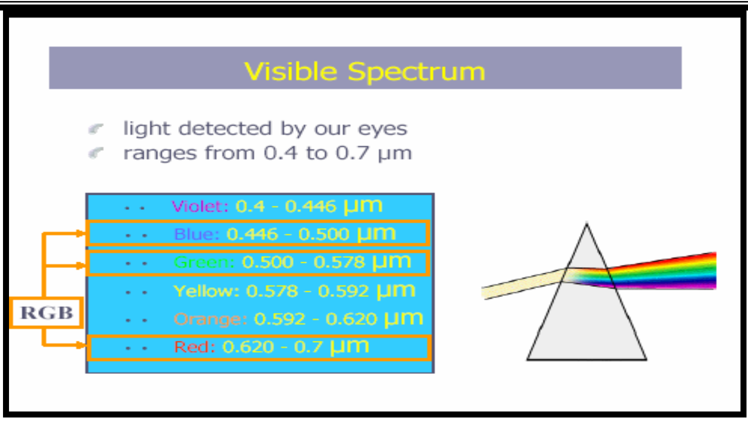


Figure (2-3) :Visible spectrum regions

2-3 Segmentation

Segmentation is the first step in the image analysis . It refers to subdividing an image into distinct regions that are supposed to correlate strongly with objects or features of interest in the image.

In general, two conditions should be fulfilled in image segmentation[19][20] :-

- Pixels that are grouped together (that belong to the same region)must have similar attributes.
- Generated regions(groups of pixels)should be meaningful.

2-3-1 Definition of Segmentation

Let I denote an image, and let P be a logical predicate which is defined as partition $S=R_1, R_2,\dots, R_n$ of I that verifies the following conditions[20]:

(i) $\bigcup_{i=1}^{N} R_i = I$

(ii) R_i is connected $\quad i=1,2,\dots.n$

(iii) $P(R_i)=True$ $\quad i=1,2,\dots.n$

(iv) $P(R_i \cup R_j)=False$ $\quad i\neq j$ for all adjacent regions R_i , R_j.

In this definition ,the first condition implies that segmentation is complete (i.e., every pixel should belong to a region) .

The second condition requires that pixels in a region are connected (i.e., regions are composed of contiguous pixels) .

The third condition determines what kind of properties the segmented regions should have (i.e., confirms that every region is homogenous and verifies the similarity criteria).

The fourth condition expresses the maximality of each region in the segmentation(i.e., affirms that a region could not be extended any more).

Verifying these conditions is consider a very difficult mission. Because real world images contain some complexity due to overlapping objects and high contrast amissibility between these regions .

In general, the segmentation process has two types of mistakes:

- The segmentation process has add new regions(i.e., region not represented actual objects in image).
- Some regions may be amissbile in region.

Therefore a fixed theory is not found in relation to segmentation problem, where all techniques found depend on ad-hoc principles in performance to segmentation process . The following are the most popular methods in segmentation process[19][20][21]:-

- Thresholding
- Boundary Detection
- Region growing
- Region splitting and Merging
- Clustering Techniques

Since we deal with the clustering techniques in this work, the following paragraph with explain them.

2-3-2 Clustering Techniques

Clustering [15][19] is a popular unsupervised pattern classification technique which partitions the input space into K regions based on some similarity or dissimilarity metric.

The number of partitions or clusters may or may not be known a priori. Let the input space S be represented by n points $\{x_1,x_2,\ldots,x_n\}$, and the K clusters be represented by $C_1, C_2, \ldots, C_K$. Then

(i) $C_i \neq 0$ for $i=1,2,\ldots, K$

(ii) $C_i \cap C_j = 0$ for $i=1,2,\ldots, K$ and $j=1,2,\ldots, K$ and $i\neq j$

(iii) $\bigcup_{i=1}^{K} C_i = S$

2-3-2-1 Elements of Clustering Techniques

In general the clustering methods include the following elements[21]:

1- Pattern representation: determines number of clusters, number of variable vectors and number of features in the feature vector.

2- Feature selection : defines a subset of features to use in clustering process.

3- Data abstraction: represents a process to find simple representation of clustering sets.

4- Assignment measure: explains how we can combine feature vectors by feature selection of one of the variable cluster. There are two types of these measures :

   a. Distance measures such as Euclidean distance, Minkowski distance .
   b. Similarity measures such as Vector inner product .

2-3-2-2 Cluster Validity Algorithms

Cluster validity – measures goodness of a clustering relative to others created by other clustering algorithms, or by the same algorithms using different parameter values. Cluster validation is a very important issue in clustering analysis because the result of clustering needs to be validated in most applications. In most clustering algorithms, the number of clusters is set as user parameter. There are a lot of approaches to find the best number of clusters[22][23][24].

(i) Dunn's Validity Index

This technique is based on the idea of identifying the cluster sets that are compact and well separated. For any partition of clusters, where c_i represent the *i*-cluster of such partition, the Dunn's validation index, *D*, could be calculated with the following formula:

$$D = \min_{1 \le i \le n} \left\{ \min_{1 \le j \le n} \left\{ \frac{d(c_{i,} c_j)}{\max_{1 \le k \le n} \{d \ (c_k)\}} \right\} \right\} \qquad \text{........................ (2-2)}$$

Where $d(c_i, c_j)$:- distance between clusters c_i, and c_j (intercluster distance); $d(c_k)$:- intracluster distance of cluster c_k ; *n*:- number of clusters. The minimum is calculating for number of clusters defined by the mentioned partition. The main goal of the measure is to maximise the intercluster distances and minimise the intracluster distances. Therefore, the number of cluster that maximise *D* is taken as the optimal number of the clusters[23].

(ii) Davies-Bouldin Validity Index

This index is a function of the ratio of the sum of within-cluster scatter to between-cluster separation.

$$DB = \frac{1}{n} \sum_{i=1}^{n} \max_{i \ne j} \left\{ \frac{S_n(Q_i) + S_n(Q_j)}{S(Q_i, Q_j)} \right\} \qquad \text{........................ (2-3)}$$

where n- number of clusters, S_n- average distance of all objects from the cluster to their cluster centre, $S(Q_i,Q_j)$- distance between clusters centres. Hence the ratio is small if the clusters are compact and far from each other.

Consequently, Davies-Bouldin index will have a small value for a good clustering[15],[22],[23]. This index is used in this work as fitness function to breeder genetic algorithm and it is explained with more detail in chapter three.

(iii) Jaccard index

This index is defined as follows:

$$J(C,K) = \frac{a}{a+b+c} \qquad \text{......................(2-4)}$$

In this index ,which has commonly applied to assess the similarity between different partitions of the same dataset ,the level of agreement between a set of class labels C and a clustering result K is determined by the number of pairs of points assigned to the same cluster in both partitions. And we can use another indexes such as Silhouette Validation Method, Goodman-Kruskal index, Isolation index and C index . For more detail see reference number[24].

2-3-3 Characteristics Of The Color Image Segmentation

Color image segmentation is typically the first and most difficult task for any automated image understanding process. It refers to extracting the connected regions satisfying similarity criteria based on the feature from spectral components defined in a color space model. Several color spaces have been examined in our search (RGB color space and HSI color space) for the most discriminating features. The consideration of multiple features increases the problem space dimensionality. And data clustering becomes a natural choice for solving the classification problem [25].

2-4 Evolutionary Algorithms(EAs)

The term Evolutionary Algorithms refers to a big family of search methods based on concepts taken from Darwinian evoluation of species and natural selection of the fittest[8]. EA maintains a population of individuals that represent potential solutions to it[4].

Each individual in the population is represented by chromosome consisting of a string of atomic elements called genes. Each gene represents a variable, either for the problem or for algorithm itself. The possible value of a gene is called alleles and gene's position in the chromosome is called locus(loci).

There is also distinction between the genotype, (i.e., the genetic material of an individual) and the phenotype, (i.e., the individual result of genotype development). In EAs the genotype coincides with the chromosome, and the phenotype is simulated via a fitness function, a scalar value-similar to a reinforcement expressing how well and individual has come out of a given genotype.

The search process usually starts with a randomly generated population and evolves over time in a quest for better and better individual where, from generation to generation, new populations are formed by application of three fundamental kind of operators to the individuals of a population, forming a characteristic a three step procedure[8]:-

1- Selection of the fittest individuals, yielding the so-called gene pool.
2- Recombination/crossover of the previously selected individuals forming the gene pool, giving rise to an offspring of new individuals.
3- Mutation of the newly created individuals.

By iterating this three-step mechanism. It is hoped that increasingly better individuals will be found. This reasoning is based on the following ideas[26]:-

1- The selection of the fittest individuals ensures that only the best ones will be allowed to have offspring, driving the search towards good solutions.
2- By recombining the genetic material of these selected individuals. The possibility of obtaining an offspring where at least one child is better than any of its parents is high.
3- Mutation is mean to introduce new rails, not present in any of the parents. It is usually performed on freshly obtained individuals by slightly altering some of their genetic material.
4- Replacement criterion is the last operation that basically says which elements, among those in the current gene-pool and their newly generated offspring, are to be given a chance of survival on to the next generation. And there are two basic strategies of replacement[27]:

   a. The plus strategy :- denoted by$(\mu+\lambda)$where the letter μ denotes the population size and the letter $\lambda > \mu$ the number of offspring to be generated out of the μ elements. In this strategy both the parents and their offspring will be taken into account to form a new generating of again μ elements.
   b. The comma strategy: - denoted by (μ, λ) the parents, after generating offspring, die off and are not taken into account to form the next generation.

From the above discussion we can conclude the following :EA may be seen as non-empty sequence of ordered operator applications (generation, fitness evaluation, selection, recombination, mutation, replacement). The entire process iterates until one of the following criteria is fulfilled[8]:

1- Convergence: - it happens because the individuals are too similar fresh and new ideas are needed, but recombination is incapable of providing them because the individuals are very close to one another, and mutation alone is not powerful enough to introduce the desired variability. Convergence can be monitored by on-line(average of the best individuals)or off-line(average of average individuals)throughout the generations.

2- Problem solved :- the global optimum is found up to a satisfactory accuracy (if optimum known).
3- End of resources :- the maximum number of function evoluation has been reached.

We can conclude that EAs are effective mainly because their search mechanism keeps a well-balanced tradeoff between Exploration (trying to always drive the search to the discovery of new, more useful, genetic material) and Exploitation(trying to fine-tune good already-found solutions). Exploration is mainly dealt with by mutation operator while Exploitation is carried out by the selection process and the use of recombination operators, although mutation may also play a role in the fine-tuning of solutions. EA can be formally described by the conceptual algorithm in algorithm(2-1)parameterized by a tuple:

$<$EA-setup$>$= $<\prod,<\mu,\lambda>, \gamma, \Omega, \Psi, \Phi, E, \theta>$

where :- $\prod$: the initial population, μ:the population size, λ :the offspring size (out of μ), γ : the selection operator, Ω: the recombination operator, Ψ: the mutation operator, θ: the termination criterion, Φ: the fitness function, E: the replacement criterion [8].

Procedure Evolutionary –Algorithm(<EA-Setup>)
{ t:=0
create Π_t
evaluate $\Phi(i), \forall_i \in \Pi_t$
While not $(\theta(\Pi_t))$ do
{/*Create the gene pool Π_t^{γ} */
Select: $\Pi_t^{\gamma} = \gamma(\Pi_t)$
/*Apply genetic operators*/
recombine: $\Pi_t^{/} := \Omega(\Pi_t^{\gamma})$
$\Pi_t^{//} := \psi(\Pi_t^{/})$ mutate:
/*Evaluate their effect*/
evaluate $\Phi(i), \forall_i \in \Pi_t^{//}$
/*Form the new generation */
replace: $\Pi_{t+1} := E(\Pi_t^{//} \cup \Pi_t^{\gamma})$
t=t+1
}
}

Algorithm (2-1): Procedure Evolutionary Algorithm(<EA-setup)

In this algorithm, operator sequencing on the population is as follows :$\prod_t$:represents the population at time t, Π_t^{γ} :the population after selection, $\prod_t^{\backslash}$: the population after recombination, $\prod_t^{\backslash\backslash}$:the population after mutation, $\prod_{t+1}$: the new population .

2-5 Breeder Genetic Algorithm

BGA introduced in Muhlenbein and Schlierkamp-Voosen 1993 is based on the science of breeding[28]. And it represents a class of random optimization techniques gleaned from the science of population genetics, which have provided their ability to solve hard optimization problems with continuous parameters[10]. BGA is in midway between GAs and ES, Figure(2-4)illustrates this. In GAs, selection is stochastic and a means to mimic to some degree Darwinian evolution. BGA selection is name truncation selection, a deterministic procedure driven by
breeding mechanism, an artificial selection method in which only the best individuals_

usually a fixed percentage T of total population size μ are selected and the gene pool to be recombined and mutated is entered, as the basis to form a new generation.

Genetic (recombination and mutations) operations are applied by randomly and uniformly selection of two parents until the number of offspring equals (μ-q). Then , the former(q)best elements are re-inserted into the population, forming a new generation of μ individuals that replaces the previous one. This guaranteed survival of some of the best individuals is called q-elitism for the BGA, the typical value is q=1[8][26].

The BGA selection mechanism is then deterministic (i.e., there are no probabilities), extinctive (the best elements are guaranteed to be selected and the worst are guaranteed not to be selected). And 1-elitist(the best element is always to survive from generation to generation)[29].

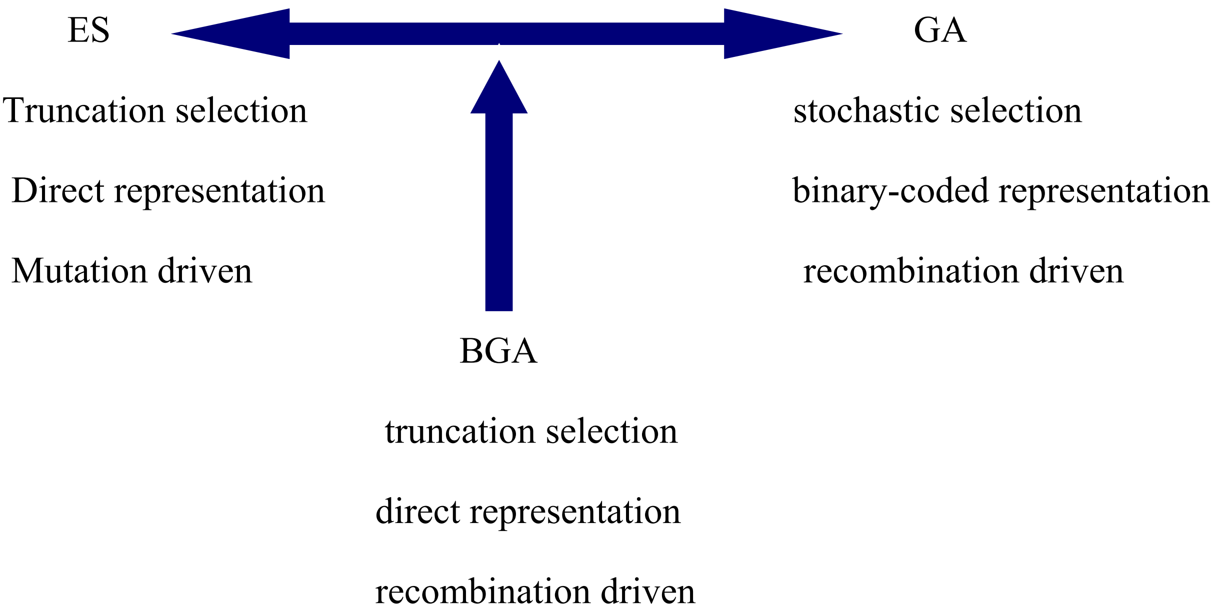


Figure (2-4): The BGA lies in the midway between ESs and GAs

Self-mating is always prohibited. The BGA procedure is depicted in Figure(2-5) unlike GAs, BGA uses direct representation, that is, a gene is a decision variable (not a way of coding it)and its allele is the value of the variable. An immediate consequence is that, in the absence of other conditionings as constraint handling, the fitness function equals the function to be optimized. In a BGA chromosome there are no additional variables, i.e., the algorithm does not self-optimize any of its own parameters , as is done in ES and in some meta GAs. Chromosomes are thus potential solution vectors $\vec{x}$ of n components where n is the problem size, the number of free variables of the function to be optimized. This issue is of crucial importance because:-

1- It eliminates the need of choosing a coding function (e.g., binary , gray).
2- It clears the way to the direct coding of different kinds of variables other than real number (e.g., fuzzy quantities, discrete quantities, etc).

The common aspect of BGA with ordinary GAs is the fact that both are mainly driven by recombination, with mutation regarded as an important but background operator intended to reintroduce some of the alleles lost in the population, this view is conceptually right for GAs, because the cardinality of the alphabet used to code variables into the chromosome (the number of alleles per gene) is usually very small (two, in most cases). But in the case of algorithm that makes use of real-valued alleles , like the BGA, mutation has to be seen in the double role of solution fine-tuner(for very small mutations)and as the main discovery force(for moderate ones)[8][26].

In most real life situations, the number of cluster in an image data set is not known a priori. Therefore, in this work, the breeder genetic algorithm is used to automatically evolve a proper number of clusters and provide the appropriate clustering of any image data set .

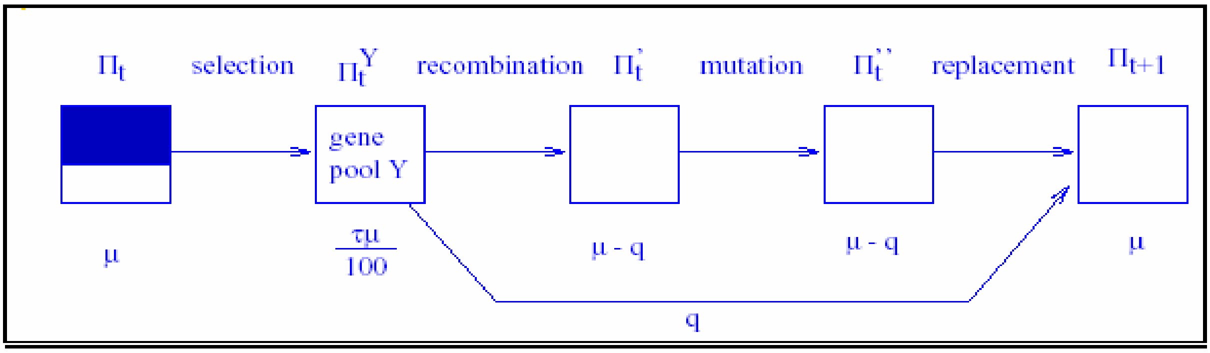


Figure (2-5) : A scheme of the BGA procedure.

Each box represents the population at different stages in the process to form a new generation. Notation on top of the boxes names the population at that point and the label from box to box (above the arrows)denotes operator sequencing (from left to right). The expressions at the bottom of the boxes indicate the population size at each step. Note how the final population size μ is formed by summing its two incoming values.

2-5-1 The Basic Schema of BGA

```
begin
    t =0
    initialise  randomly μ(t) with μ individuals
      while (termination criterion not fulfilled) do
          evaluate goodness of each individual
          save the best individual in the new population
          select the best τ % individuals
          for i=1 to μ-1  do
            select randomly two elements within the best τ% in μ(t)
            recombine them so as to obtain one offspring
            perform mutation on the offspring
            insert it in μ'(t)
          end for
         μ(t+1)= μ'(t)
         t=t+1
         update variables for termination
      end while
  end
```

Algorithm(2-2):Breeder Genetic Algorithm

2-5-2 The Elements Of BGA

2-5-2-1 Evaluation

EA assigns fitness value for each individual generated in the initial population or during the following generations. This value is connected with the value of objective function, e.g. Fitness value of maximization problems equals to objective function while for minimization problems the target is to find the solution which has minimum value of objective function, therefore the solution which has the mimic value of objective function gets maximum fitness value[21]. And we can use the following transform of objective function for these type of problems

$$\text{Fitness}=\frac{1}{(1+f(x_1,x_2,\ldots,x_D)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2\text{-}5)$$

Where $f(x_1,x_2,\ldots,x_D)$ is objective function and D is the number of decision variables in objective function.

2-5-2-2 Selection

BGAs, unlike GAs which model natural evolution, are based on a scheme driven by the breeding selection mechanism. The selected elements are let free to mate(self-mating is prohibited) so that they generate a new population. The former best element is then inserted in this new population (elitism)and the cycle of life continues[29].The selection scheme is the truncation model: in it, starting from a population of μ individuals ,only $\mathcal{T}$% elements showing the best fitness are chosen to give origin to the individuals of the next generation and $\mathcal{T}$% is called the truncation rate and its typical values are within the range (10% to 50%)[10].

Once chosen these ($\mathcal{T}$% * μ individuals, two elements among them are randomly and equiprobabilistically selected and let mate so as to generate a new element and this is to be replaced(μ-1)times[29]. By doing so, the best elements are treated as (super-individuals) and mated together, hoping that this can lead to a fitter population (these concepts are taken from other sciences and mimic animal breeding) [10].

2-5-2-3 Recombination

Any operater **Ω** combining the genetic material of the parents is called a recombination operator. In BGAs recombination is applied unconditionally, pr (**Ω**). let $\vec{X}=(x_1,x_2,\ldots,x_n)$, $\vec{y}=(y_1,y_2,\ldots,y_n)$ be two selected gene-pool individual $\vec{x}$, $\vec{y}$ such that $\vec{x} \neq \vec{y}$. Let $\vec{z}=(z_1,z_2,\ldots,z_n)$be the result of recombination and $1 \le i \le n$. The following are some of the more common possibilities to obtain an offspring[8],[26],[29].

1- Discrete Recombination

$Z_i \in \{x_i, y_i\}$ ……………………(2-6)

chosen with equal probability

2- Extended Line Recombination

$Z_i = x_i + \alpha (y_i - x_i)$, where $y_i \ge x_i$ ……………………(2-7a)

$Z_i = y_i + \alpha (x_i - y_i)$, where $y_i < x_i$ ……………………(2-7b)

With α uniformly random chosen in [-d,1.0+d] where d is a parameter for the BGA and $d \ge 0$ (typical d=0.25).

3- Extended Intermediate Recombination

$Z_i = x_i + \alpha_i (y_i - x_i)$, where $y_i \ge x_i$ ……………………(2-8a)

$Z_i = y_i + \alpha_i (x_i - y_i)$, where $y_i < x_i$ ……………………(2-8b)

With α_i uniformly random chosen in [-d,1.0+d] the difference with ELR being that in this latter case we choose a new α_i for each i.

4- Fuzzy Recombination

It is based on ideas borrowed from the fuzzy set theory and this operator basically replaces the uniform pdf (probability distribution function)by a bimodal one where the two modes are located at x_i and y_i the two parents, that is $Pr(z_i) \in \{Pr_{xi}(z_i), Pr_{yi}(z_i)\}$ thus favoring offspring values close to them, and not in any intermediate point with equal probability, as with previous operators. The label "fuzzy" comes from the fact that the two parts $Pr_{xi}(t)$, $Pr_{yi}(t)$ of the probability distribution resemble fuzzy numbers(triangular in the original formulation), such that they fulfill the general conditions(where $y_i \geq x_i$) [26].

$$x_i - e|y_i - x_i| \leq t \leq x_i + e|y_i - x_i|$$
$$y_i - e|y_i - x_i| \leq t \leq y_i + e|y_i - x_i| \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2\text{-}9)$$

stating that the offspring t lies in one or (both)of intervals, being (e > 0) the fuzzy numbers spread, the same for both parts the favour for offspring values near the parents is thus stronger the closer the parents are, this operater is depicted in figure(2-6). Where the distribution is a symmetric bimodal with a median equal to $(\frac{(x_i + y_i)}{2})$

The membership function of a normalized triangular fuzzy number with mode m and symmetric spread S(left-right distance from modes)is

$$\mu(t)_T\{s, m\} = 1 - \frac{2|m - t|}{s} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2\text{-}10)$$

whereas the corresponding unimodal triangular pdf is :-

$$\Pr(t)_T\{s,m\} = \begin{cases} 0 & t < m-s \\ \frac{1}{s^2}(t+s-m) & m-s \le t \le m \\ \frac{1}{s^2}(-t+s+m) & m \le t \le m+s \\ 0 & t > m+s \end{cases}$$ ....(2-11)

In the simplest case ,assuming e=0.5 (that is ,the two parts meet at the median and this point has zero probability, the resultant parameterized bimodal traiangular pdf is written

$$\Pr(t)_{BT}\{s_1,m_1,s_2,m_2\} = \frac{1}{2}(\Pr(t)_T\{s_1,m_1\} + \Pr(t)_T\{s_2,m_2\})$$ ...(2-12)

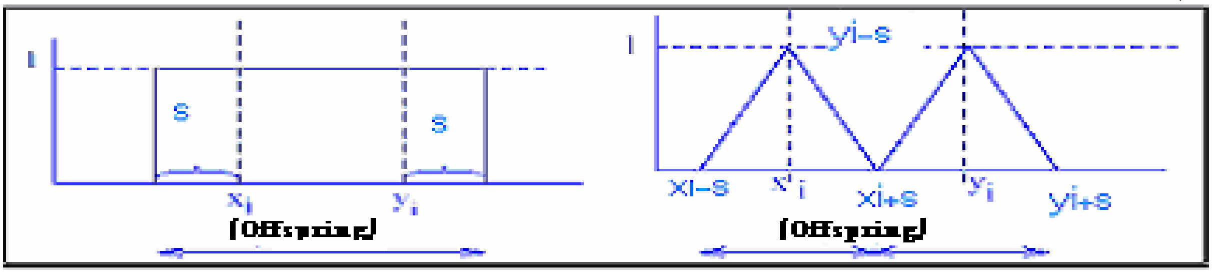


Figure (2-6) : potential zones for offspring and their probabilities (left)for the EIR operator , uniform pdf with $s=\alpha_i|y_i-x_i|$. (Right) bimodal pdf for the FR operator ,where $s= e|y_i-x_i|$ for $0<e<1$ (show for e=0.5)

2-5-2-4 Mutation

Mutation is applied to each gene with some probability Pr(Ψ)=1/n so that ,on average ,one gene is mutated for each individual. Let $\vec{z}=(z_1,z_2,\ldots,z_n)$ be the result of mutation of an individual $\vec{x}$ $(1\le i\le n)$,the elements of $\vec{z}$ are formed as following [8][29].

1- Discrete Mutation

$$z_i' = z_i \pm \text{searchinterval}_i \cdot \text{Const.} \sum_{j=0}^{k-1} Qi \cdot 2^{-j}$$ ....(2-13)

In the above formula k is a parameter originally related to the machine precision, (i.e., the number of bits used to represent a real variable in the machine). We are working with (e.g. 24, 32, and 64). And const determines the maximum half–width of the interval centered in zi in which z_i' can be. In this work the searchinterval is represented the width and height of the image and const represented half-width, half-height of image.

Furthermore each Qi equal (zero) before mutation and is mutated to(one)with probability (1/k), so on average just one of the elements in the sum with be non-zero after mutation. A practical assumption is that we deterministically flip just one and only one of these bits, so that the above formula becomes

$z_i'=z_i \pm \text{searchinterval}_i \,.\, \text{const.}\ 2^{-j}$ ……………………(2-14)

where $0 \leq j \leq k-1$.

2- Continuous Mutation

$z_i'=z_i \pm \text{searchinterval}_i \,.\, \text{const.}\ 2^{-\beta k}$ ……………………(2-15)

Where β is a real value randomly chosen in [0,1],and k and const are as before [8][26][29].

2-5-2-5 Statistical Measures

Stop criterion or statistical measures are methods used to know convergence range of the EAs where number of these measures are found.

1- On-Line Performance

It is a measure of the average performance of EA which depends on the fitness function and the following mathematical form

$$\text{On-line}(T) = \sum_{t=1}^{T} f(T) \,/\, T \qquad \text{……………………(2-16)}$$

T : total number of the current genetic iteration

f(t) : fitness value performed on the genetic

Through breeder genetic algorithm performed, the average fitness value reaches, during number of generation , to the relatively convergence values and this means the populations are convergence [8][21][30].

2- Off-Line Performance

It is similar to the prior method but it depends on the best fitness as follows:

$$\text{Off-line}(T)= \sum_{t=1}^{T} F_{\max} \; / \; T \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2\text{-}17)$$

Where F_{max} =best{f(1),f(2),………,f(t)}

The function F_{max} calculates the best prior fitness and the function Off-Line (T) calculates the average best prior fitness. Therefore in this work can depend on this measure to know algorithm, convergence range, by reminding that there is value relative fixed through limited number of generation [8][21][30].

2-5-3 Image Segmentation and Evolutionary Algorithm

EA is considered from modern applications that used in image segmentation which has been suggested by Researchers to obtain a good performance to solve segmentation problem. One of the reasons that led researchers to use EA as segmentation method is the ability of EA to deal with complex and big search space provided that little knowledge should be available about application space. Most segmentation algorithms including many parameters that must be adjusted to get the desired performance. Additionally, they include complex interaction among those parameters. These two issues have relatively complicated the search space. The segmentation problem is formulated as a clustering problem which means that the solution suggested to the problem of clustering are at the same time solutions to segmentation problem. The best method to represent clustering problem is (centeroid –based), where chromosome contains M genes and each gene represents cluster center that takes the form vector which identifies K features as in Figure (2-7). The suggested method uses this representation .

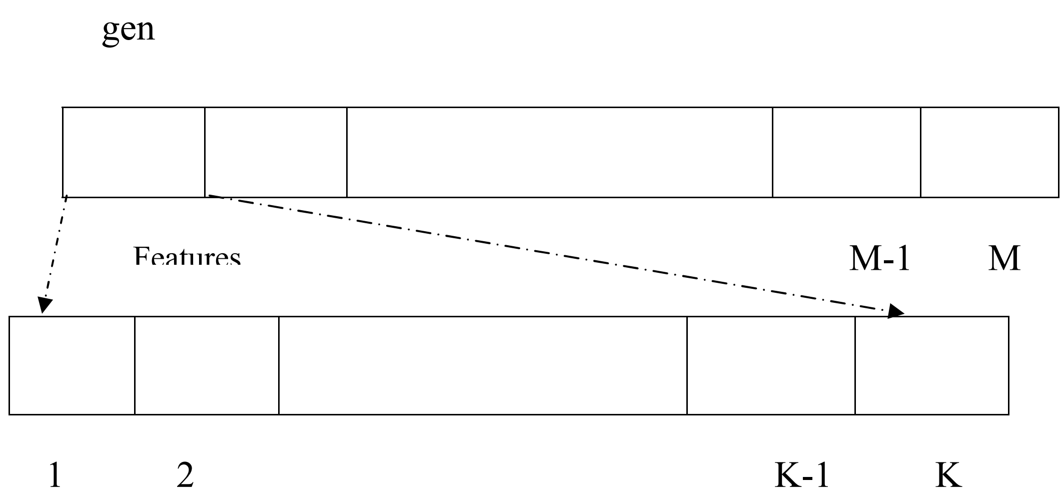


Figure (2-7) : representing chromosome centroid-based

2-6 Artificial Neural Networks

Neural networks have been increasingly popular as a means of processing information. One of the reasons for this popularity is their learning abilities. Recent development of powerful learning algorithms for parallel distributed network has made it possible to program computer in a new way.

These new techniques allow for program massively parallel network by examples rather than by algorithms; i.e., the user does not program a neural network, but he teach it[31].

There is no universally accepted definition of an ANN. However, most people in the field would agree that an ANN is a network of many simple processors("units") , each possibly having a small a mount of local memory. The units are connected by communication channels("connections")which usually carry numeric (as opposed to symbolic)data, encoded by various means. The units operate only on their local data and on the inputs they receive via the connections. A neural network is characterized by:

1- Its pattern of connections between the neurons (units), called its architecture.
2- Its method of determining the weight on the connections, called its training, or learning algorithm)
3- Its activation function.

ANN can be applied to a wide variety of problems, such as storing and recalling data or patterns, classifying patterns, performing general mapping from input patterns to output patterns, grouping similar patterns, or finding solutions to constrained optimization problems[9].

ANNs have been developed as generations of mathematical models of human cognition, and they have the following benefits[32]:

- Ability to tackle new kinds of problem
- Robustness
- Fast processing speed
- Flexibility and ease of maintenance
- Non-linearity
- Interpolation of data
- No need for a model

Neural network architectures cover a wide range in ANN. Where each computer is a neural net, because we can view traditional digital logic as constructed from interconnected neurons [33].

McCulloch and Pitts in 1943 year suggested the first model of neuron based on the highly simplified consideration of the biological model and it's use of threshold principle of the neuron suggest the meaning that the output of neuron is binary(0,1)and the firing rule for this model is defined[34]

$$o^{k+1} = \begin{cases} 1 & \text{if } \sum_{i=1}^{n} W_i X_i^k \geq T \\ 0 & \text{if } \sum_{i=1}^{n} W_i X_i^k < T \end{cases} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2\text{-}18)$$

Where Xi: inputs, for i=1,2,…..,n. and o^{k+1} : denoted the neuron output at instant k. For more detail see references [9][33][34].

At 1949 Donald Hebb designed the first learning law for artificial neural network. His premise was that if two neurons were active simultaneously then the strength of the connection between them should be increased [9].

Rule text is "when an axon of cell A is near enough to excite a cell B and rapidly or persistently takes place in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased " [34] , and this rule represents the basic rule for many learning rules used to training artificial neural network to adjusting the connection weight of neurons[35]. There are many applications of neural networks in general area such as signal processing ,control, pattern recognition, medicine, speech production, speech recognition and optimization problems[9][34].

2-6-1 Motivation For Using Neural Networks

1- Parallelism:- parallelism is fundamental in the architecture of neural networks. This parallelism is interesting because of the limitations of sequential methods for processing large problems needing an enormous quantity of data and computational time and specialization in arithmetic or transfer operations that are performed frequently.
2- Capacity of adaptation:- a highly important feature of the neural network is their ability to learn to solve a problem without being programmed, which gives the network the ability to adapt and continue learning new things from the external world as they arise.
3- Capacity of generalization :- it is highly significant to consider a system which may learn the rules simply from a set of examples, or which may learn to mimic a behavior. It is important to note that artificial neural network generalized automatically as a result of its structure. This generalization is limited to a certain degree.
4- Fault tolerance:- the neural network has many processing nodes, each with primarily local connections and damage to a few nodes or links will not impair overall performance significantly[31][35][9].

2-6-2 Type of Neural Networks

Neural network neurons are arranged in layers .Typically , neurons in the same layer behave in the same manner. Key factors in determining the behavior of a neuron are its activation function and the pattern of weighted connections over which it sends and receives signals. The arrangement of neurons into layers and the connection pattern within and between layers is called the net architecture[9]. Neural network architectures which depend on general structure are classified into three classes.

1-Feed Forward Network

FFN consists of one layer or more from nonlinear processing elements or neurons. The neurons determine layer connecting with neurons in neighboring layer through sum of neural connections. And the information flows in this type of network by one side from input layer to output layer, and the learning type used in this network is supervised learning, back propagation neural network is more popular and uses this type of network .

2-Feedback Network

In this type of network the neurons connect together where the output of each neuron connects with inputs of other neuron in the same layer and neighboring layer. The inputs define the initial state of neural network and neuron states change reaching to equilibrium state represented by minimum energy to become neuron states comporting to actual output. One of the types of this type of network is Hopfield network[30][34].

3-Competitive Networks

CN discovers relations between training patterns through clustering process of training patterns to similar clustering patterns, where each pattern is assigned to a near cluster through measuring the distance between pattern and different clustering centers and the network produce representative vector for each clustering representing class center. The learning in this network is unsupervised learning therefore this network is called self-organization networks. Of the popular types of this type of network are cluster discovery network and self-organization features map [9][34].

2-6-3 Learning in Neural Network

Learning in neural network is a more direct process, and we typically can capture each learning step in a distinct cause-effect relationship [34]. Learning in ANN is accomplished by using examples [30][36], and it is achieved by adjusting the connection weights in ANNs. The essence of a learning algorithm is the learning rule ,i.e., a weight updating rule which determines how connection weight are changed. Examples of popular learning rules include the delta rule, Hebbian rule ,anti-Hebbain rule, and the competitive learning rule[36]. The classification of learnings are based on whether the learning stages are done in the presence of supervisor "teacher" or not [31]:-

2-6-3-1 Supervised Learning

Supervised learning is based on direct comparison between the actual output of an ANN and desired correct output, also known as the target output. It is often formulated as the minimization of an error function such as the total mean square error between the actual output and the desired output summed over all a variable data[36].

In supervised learning, we assume that at each instance of time when the input is applied, the desired response of the system is provided by the teacher [34]. Therefore, in this type of learning you must exists a "teacher" or "trainer". This is the form of learning which is best understood ,and presently most suitable to real supervised learning applications[31]. Back propagation network is example of networks which used these kind of learning . The block diagram of supervised learning is shown in Figure(2-8).

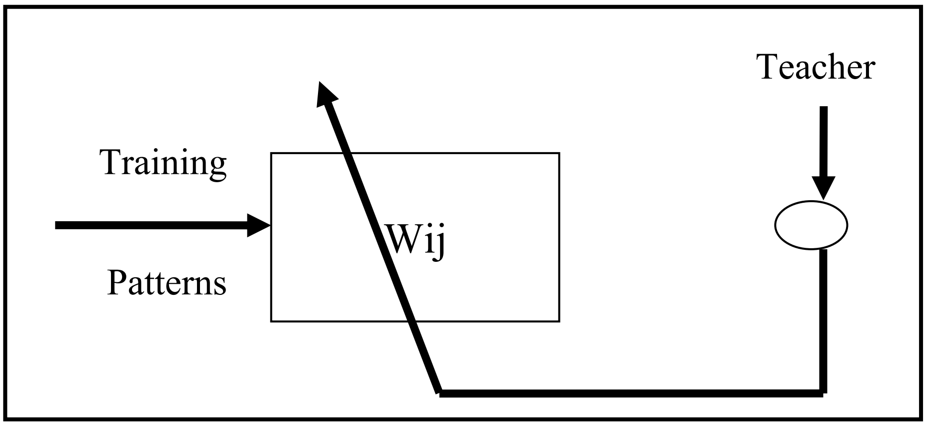


Figure (2-8): supervised learning

2-6-3-2 Reinforcement Learning

Reinforcement learning is a special case of supervised learning where the exact desired output is unknown. It is based only on the information of whether or not the actual output is correct[36]. And we can consider Reinforcement learning as a middle stage between supervised learning and unsupervised learning[35]. Self-organization map is an example of networks that used this learning.

2-6-3-3 Unsupervised Learning

Unsupervised learning is solely based on the correlations among input data. No information on "correct output" is available for learning [36]. Unsupervised learning is sometimes called learning without a teacher [31][34].

The technique of unsupervised learning is often used to perform clustering as the unsupervised classification of objects without providing information about actual classes. This kind of learning corresponds to a minimal priori information variable. Some information a bout the number of clusters, or similarity versus dissimilarity of patterns, can be helpful for this mode of learning [34]. Hopfield network is an example of networks that used this kind of learning. The block diagram of unsupervised learning is shown in Figure (2-9).

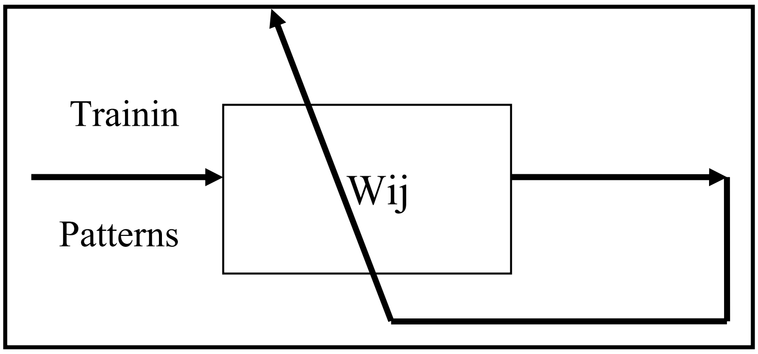


Figure (2-9) : Unsupervised Learning

2-6-4 Activation Functions

The summing activation is a basic operation of an artificial neuron which involves its weighted input signal and applying an output, or function. For input units, this function is the identity function.

In order to achieve the advantages of multilayer nets, compared with the limited capabilities of single-layer nets, nonlinear functions are required (since elements with linear activation functions are not different from what can be obtained when using a single-layer)[31].

2-6-4-1 Global Activation Function

These functions are distinguished by dividing their input into infinite regions such as :-

1- Sign Function

The output of this function depends on input signal and it is a simple function and not derivative therefore most learning algorithms depending on derivative ones cannot use this function. Sign function is divided into two types[9][30]:

i. Unipolar Binary Function

$$F(net) = \begin{cases} 1 & \text{if net} \geq 0 \\ 0 & \text{if net} < 0 \end{cases} \qquad \text{.........................(2-19)}$$

This function is called also (Heaviside function)and its output is binary values(0,1) , as explain in Figure (2-10).

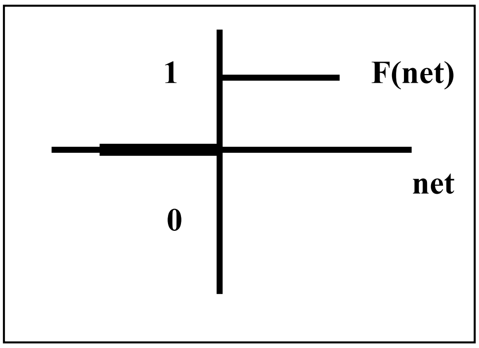


Figure (2-10): Unipolar Binary Function

ii. Bipolar Binary Function

$$F(net) = \begin{cases} +1 & \text{if net} \geq 0 \\ -1 & \text{if net} < 0 \end{cases} \qquad \text{.........................(2-20)}$$

This function is also called (Signum function)and its output is binary values(+1) or (-1), as explain in Figure (2-11).

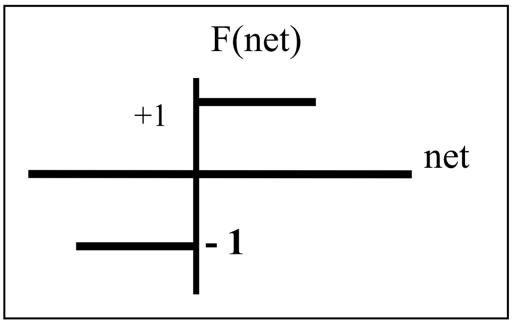


Figure (2-11) : Bipolar Binary Function

In general the sign function is called (HARD limiting activation function)[34].

2- Sigmoidal Function

It is a popular function used in many learning algorithms because it is nonlinear function and derivativable [35]. Sigmoidal functions(S-shaped curves)can be divided into two types:-

i. Unipolar Sigmoid Function

$$F(net)=\frac{1}{1+\exp(-\lambda net)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2\text{-}21)$$

The output of this function lies in the range [0,1]where the net is the summation input of neurons , $\lambda>0$ and λ determining the steepness function F(net)near net=0, if $\lambda\rightarrow\infty$ then the function near from step function [30][34][35]. Definition in relation (2-21) . This function is sometimes called (logistic function)[9]. Figure(2-12)shows this function.

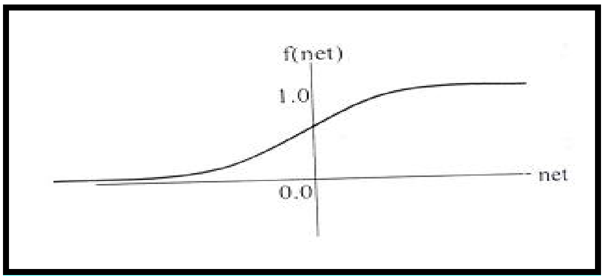


Figure (2-12) : Unipolar Sigmoidal Function

ii. Bipolar Sigmoid Function

$$F(net) = \frac{2}{1 + \exp(-\lambda\ net)} - 1 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2\text{-}22)$$

The output of this function lies in the rang[-1,+1], and it is also called (Hyperbolic Targen Function) [9][30]. Figure(2-13)shows this function .

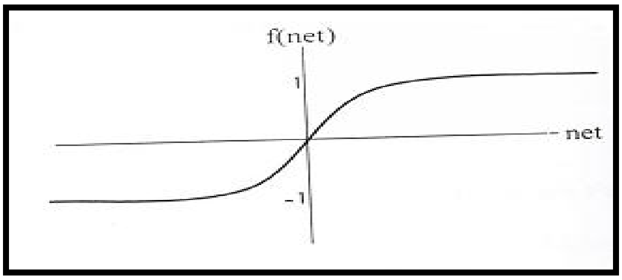


Figure (2-13) : Bipolar Sigmoidal Function

2-6-4-2 Local Activation Function

This function can be considered as replacement of prior function and its applied to local field from input and it's divided into two types [9][30][35].

i. Pulse Function

$$F(net) = \begin{cases} +1 & \text{if } a \le net \le b \\ 0 & \text{otherwise} \end{cases} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(2\text{-}23)$$

This function uses two parameters to represent lower and upper input values. The problem of this function is that it can't be derivative, therefore we can't use it in learning algorithms depending on the derivative. Figure(2-14)shows this function .

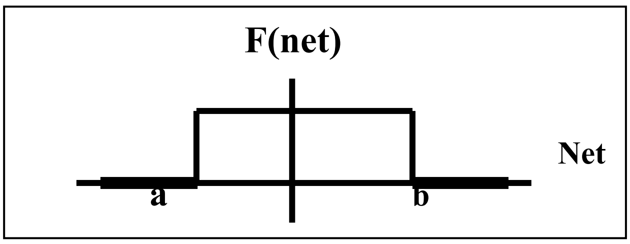


Figure (2-14): Pulse Function

ii. Gaussian Function

$$F(net) = \exp\left(\frac{-(net - c)^2}{2\sigma^2}\right) \qquad \text{........................(2-24)}$$

Where:- net :inputs to Gaussian function , σ : stander deviation, c : mean value.

This function is derivative therefore we can use it in learning algorithms depending on derivative. Figure(2-15)shows this function .

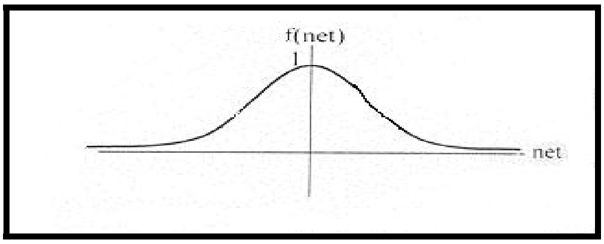


Figure (2-15) : Gaussian Function

2-6-5 General Structure of Connections

The human brain consists of a large number (more than a billion)of neural cells that process information. Each cell works like a simple processor and only the massive interaction between all cells and their parallel processing makes the brain's abilities possible [32].

Many biological studies applied to human brain have found a large number of connections, and many researchers explain the shall brain is divided into a sum of layers, each layer contains a large number of neuron, and the neuron in each layer connected with the neuron in other layers to compose a complex neural system [30]. ANN can be divided into two types depending on their structure.

1- Layered Network

This network contains a set of successive layers and each layer contains a set of neurons, and the neuron in neighbored layers connects with others, we can distinguish three type of layers :-

a. Input Layer

Input layer is accountable of revised stimutatation that introduce to network.

b. Hidden Layer(s)

ANN usually contains one hidden layer or a set of successional layers doing on extraction features respectively by stimutatation patterns.

c. Output Layer

Output layer is accountable of expressing the network outputs .

Example of the layer networks (perceptron neural network and back propagation network).

2- Fully Connected Networks

In this type of networks, each neuron is connected with itself and with all other neurons in the network where we can find two connections between all the neighboring neurons with two sides and this gives the network the ability to be recursive, because the output of each neuron becomes input into the other neuron in the same layer or in other layer and this helps the network to access to the balance state, example of it is Hopfield network.

2-7 Back Propagation Neural Network

Back propagation(BP) was originally introduced by Paul Werbos in 1974, David Parker in 1984/1985 and David Rumelhart, Banal Williams and other member of the Parallel Processing(PDP) group in 1986[37].

Back propagation is a systematic method for training multilayer artificial neural network and its learning rule is generalized from Widrow-Hoff rule for multilayer networks, the Back propagation network is a very popular model in neural network. It does not have feedback connections, but error are Back propagated during training, Least mean squared error is used[38]. Many application can be formulated by using a Back propagation network and the methodology has been a model for most multilayer neural networks[31].

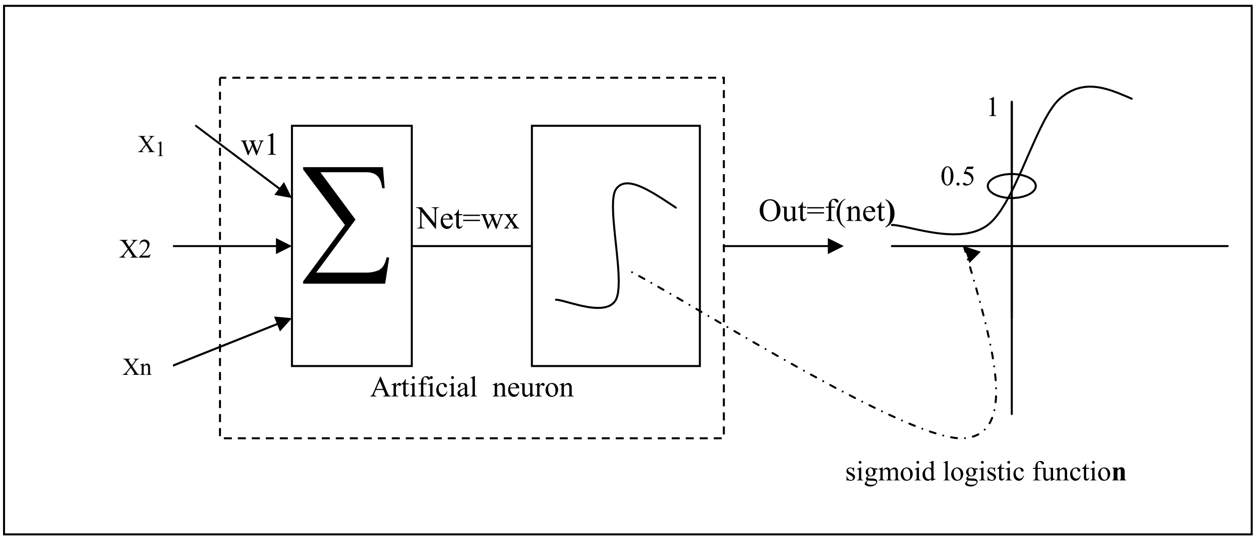


Figure (2-16): the basic Back propagation processing unit

The processing unit or neuron used here is similar in nature to the perceptron cell: it applies in activation function to the weighted sum of the inputs, the activation function is a non-linear function . A sigmoid function is most commonly Used:
out=f(net)=1/1+exp(-net) , as shown in Figure(2-16).

Errors in the output determine the measures of hidden layer output errors, which are used as a basis for adjustment of connection weights between the input and hidden layers. Adjusting the two sets of weights between the pairs of layers are recalculating the outputs in an iterative process that is carried on until the errors fall below the tolerance level[31][38].

2-7-1 Network Architecture

Error back propagation neural network consists of three kind of layers:-

1- Input Layer :- This layer is accountable for received network inputs and is distributed on hidden layer neurons .

2- Hidden Layer :- This layer does extraction information about distribution features within the sum of training examples and it's sent to a neighboring hidden layer or output layer, where we can use more than one hidden layer, but this lead to increasing complexity of network, and the difficulty lies in determining a number of hidden layers and a number of neurons in each layer. Many researchers explain the artificial neural network with one hidden layer and enough number of hidden neurons training by using error back propagation neural network able on approximation any function to accuracy and this refers to a universal approximation theorem [34][35].

3- Output Layer :- This layer is responsible for receiving stimulus pattern code from the hidden layers and finding the actual output of the network. An additional neuron is used for each of the hidden layer and output layer. This neuron is called bias or threshold unit which has a fixed value that equals (1) or (-1). It connects with all the neurons of the following layer. The weights of this neuron are trained with all the other weights of the network. Figure (2-17) explains this network [30].

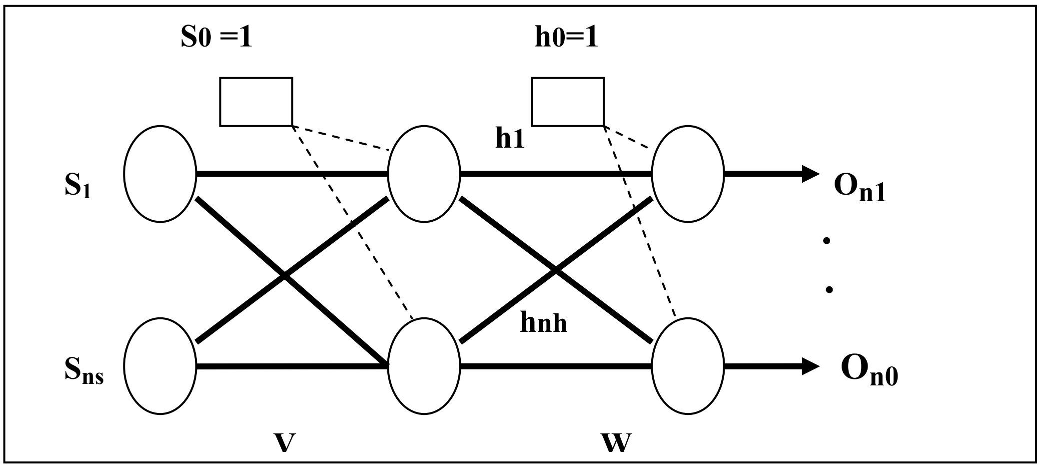


Figure (2-17) : Error back propagation network

Where: -

s_i : outputs of input neuron i.

h_k :outputs of hidden neuron k .

o_j : outputs of output neuron j.

V : weight matrix connected between input layer and hidden layer.

W : weight matrix connected between hidden layer and output layer.

n_s : number of input neurons.

n_h :number of hidden neurons.

n_o: number of output neurons.

2-7-2 The Back Propagation Learning Algorithm

The error back propagation learning algorithm is a form of supervised learning used to train mainly feed forward neural networks to perform many tasks [39]. It's used sigmoid function to determine activation of their neurons and it uses the least mean square error as a measure to determine convergence of network outputs toward the desired output [35].

$$E= \frac{1}{2} \sum_{p=1}^{P} \sum_{j=1}^{n0} (d_j^p - o_j^p)^2 \qquad \text{……………………(2-25)}$$

Where:-

E :- total error of network after input all patterns.

n_0 :- number of output neurons.

p :- number of training patterns.

d_j^p :- desired output from neuron k to training pattern p.

O_j^p :- actual output of neuron k to training pattern p.

The above derivative of cost function is used to adjust neural network weights toward the decrease of total error value of network[34].

In outline ,the algorithm is as follows :-

1- Initialization the weights of the network are initialized to small random values.
2- Select the next training pair from the training set, apply the input vector to the network input and specify the desired output vector.
3- Calculate the actual outputs of the network.
4- Calculate the error between the actual output of network and the desired output (the target vector from the training) .
5- Adjust the weights of the network in a way that minimizes the error.
6- Repeat steps 2 through 5 for each vector in the training set until the total error for the entire set is acceptable[34],[39].

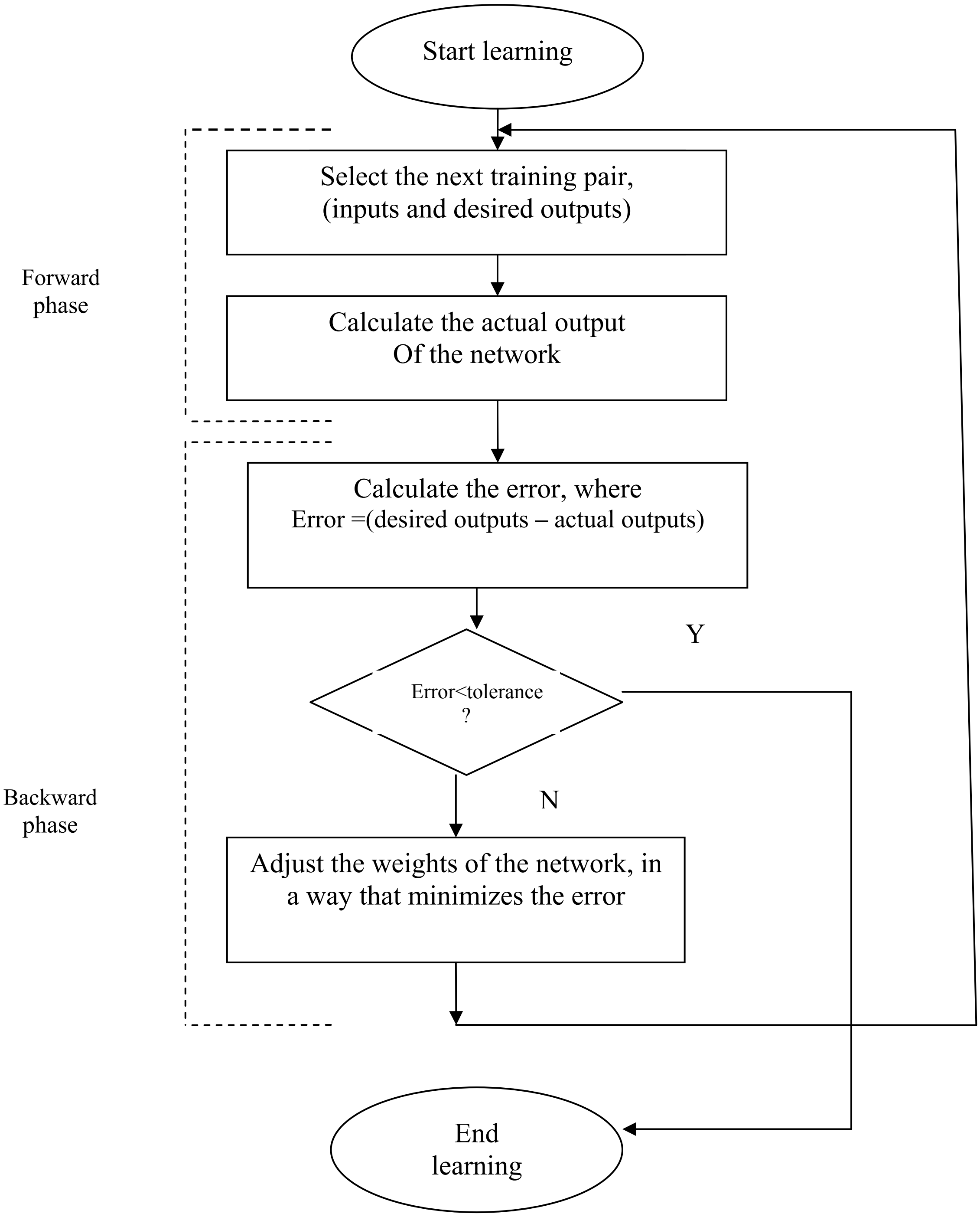


Figure (2-18) : Back propagation learning flowchart

1- Forward pass

The input of each training pattern is presented to the network . The outputs are completed using the inputs and the current weights of the network. Certain statistics are kept from this computation ,and used in the next phase . The target output from each training pattern is computed with the actual activation level of the output units. The difference between the two is termed the error, training may be pattern-by-pattern or epoch-by-epoch. With pattern-by-pattern training, the pattern error is provided directly to the backward pass. With epoch-by-epoch training, the pattern error is summed across all training patterns, and the total errors are provided to the backward pass [39]. The layer's output computed as follow[34]

$$hk = F(net_k) = F\left(\sum_{i=1}^{ni} S_i . V_{ik}\right) \quad ,\text{where } k=(1,2..,n_h) \qquad \ldots\ldots\ldots\ldots(2\text{-}26)$$

$$Oj = F(net_j) = F\left(\sum_{k=1}^{nh} h_k . W_{kj}\right) \quad ,\text{where } j=1,2..,n_j \qquad \ldots\ldots\ldots\ldots(2\text{-}27)$$

S_i :- outputs of input neuron i include threshold neuron S_0=1 .

h_k :- outputs of hidden neuron k include threshold neuron h_0=1 .

V_{ik} :- connected weight between input neuron i and hidden neuron k .

W_{kj} : - connected weight between hidden neuron k and output neuron j .

F(netj) :- activation function of neuron j .

F(netk) :- activation function of neuron k .

n_j :-number of neural in output layer .

n_h :- number of neural in hidden layer .

2- Backward pass

In this phase, the error values are calculated for all processing units and weight changes are calculated for all interconnections. The calculations begin at the output layer and process backward through the network to the input layer[31][34]. Continue doing forward and backward passes until the stopping criterion is satisfied [39] .

2-7-3 Back Propagation Neural Network Problems

Error back propagation neural network is a very effective method to solve many problems but it has some limitations or problems[30][35]:-

1- Design problem

It has unavailable limited rules to determine suitable design to the network and requisite to solve problem. The suitable design namely determines the number of hidden layers and number of hidden neurons in each layer. And it determines connection between hidden neurons and determines general connections of the network. Often we use trial and error method or other methods such as evolutions algorithm in network design process.

2- Convergence

Network training process is not an easy task (i.e., access to minima error possible) because cost function space contains features that prevent the algorithm from convergence such as many local minima. Learning rate has a high effect on convergence speed (explained in paragraph 2-7-4)to remove local minima problem that effects neural network convergence speed, we can use simulated annealing or evolution algorithm.

3- Generalization

It means, that the ability of network in learning new patterns (small difference) and not using it within training pattern set generalization constitute on important measure to prove that network is effective, especially when used in classification system.

4- Premature Saturation

As a result of many reasons choosing high initial weights, the network neurons can not learn the training patterns. These weights which represent the input to the neuron grow constantly to get higher values which make the neuron's outputs close to the highest or the lowest value (one or zero) . All this occurs when a unipolar sigmoid function is used. Thus, the value of the derivative approximates to zero.

This in turn leads to keeping the weights fixed and eventually the error value remains high as well. Moreover, the neurons reach the saturation state.

2-7-4 Learning Factor

The effectiveness and convergence of the error back propagation learning algorithm depends significantly on the value of the learning factor η . And it's value lies in the rang [0,1].

In general the optimum value of η depends on the problem being solved, and there is no single learning factor value suitable for different training cases[34]. Therefore it is very important to choose a suitable learning factor value because if the η is very small, then the algorithm proceeds slowly, but accurately follows the path of a steepest decent in weight space, while if η is largish, the algorithm may oscillate ("bounce off the canyon walls") or overshooting[39].

Therefore, researchers used variable values of learning factor one of this method starting with using high value of learning factor and then these values decrease with the continuous learning process as follows[30].

$$\eta = \eta_0 .(1 - \frac{t}{T\ max}) \qquad \text{……………………(2-28)}$$

where:-
η :- new value of learning factor.

η_0 :- initial value of learning factor.

t :- current epoch value .

T_{max} :- max number of learning epochs.

Chapter Three

Development System to Classify Objects for Air Photos & Satellite Images

3-1 Introduction of the Proposed System

Analysis of remote sensing imagery involves the identification of various targets in an image, and those targets may be environmental or artificial features which consist of points, lines, or areas. Targets may be defined in terms of the way they reflect or emit radiation. This radiation is measured and recorded by a sensor, and ultimately is depicted as an image product such as an air photo or a satellite image.

The classification task of remote sensing imagery(i.e., air photo or a satellite image) is consider a very accurate and important mission because these imageries are able to present copious information, we can benefiting from in different domains.

Therefore, a suitable techniques to assure a correct classification to the objects in these images should be selected.

In this work, we present an approach to solve classification problems that combines supervised and unsupervised learning techniques. In unsupervised learning such as clustering, the task is to segment unlabeled training data into clusters that reflect some meaningful structure in the data. In supervised learning, it is assumed that we are given a set of labeled training points, and the task is to construct some function that will correctly predict the labels of future points according to problems that feed forward network suffer from (convergence, generation, design, premature saturation)that are explained in chapter two, paragraph(2-7-3).

Therefore, Development System to Classify Objects for Air Photos and Satellite Images (DSCOAPSI) combines many techniques, the first of which is the evaluation algorithm represented by breeder genetic algorithm that is recognized by the ability to solve the local minimum problem(premature saturation)because it starts with more than one solution. This increases the avoidance of falling in that problem. It uses truncation selection and this is suitable to find the optimal solution.

The second is feed forward neural network trained by error back propagation algorithm is used to find the class for each feature vectors. While the third technique IF-Then Rule which is used to form several rules, that govern each class attributes (i.e., specify a certain class attributes).

The suggested system in this study is implemented to solve the classification problem of air photos and satellite images. The system starts with building a database for describing five objects in the image(urban area ,forests, roads, rivers, football stadiums). Then, it uses BGA to perform a clustering process for the image and providing us with number of clusters. After that, two types of features are extracted (descriptive and statistical) from each cluster. Then, these features are represented by vectors of their values. Next, these vectors are used to train the neural network to determine the class for each vector of features. Last, by using IF –Then Rule form, several rules are formulated to govern the features of each class. Figure(3-1)shows block diagram of proposed system.

The proposed system is characterized by the following:-

1. it builds database describe each object depend on their features.
2. It uses EA(combines between features of genetic algorithm (GA)and evolution strategies (ESs))represented by BGA.
3. It uses one of cluster validity algorithms represented by David-Bouldin index(DBI).
4. It uses dynamic length of the chromosome.
5. It works in two environments which are unsupervised(clustering)and supervised(classification).
6. it formulates rules that govern features for each class by using (IF -Then Rule).

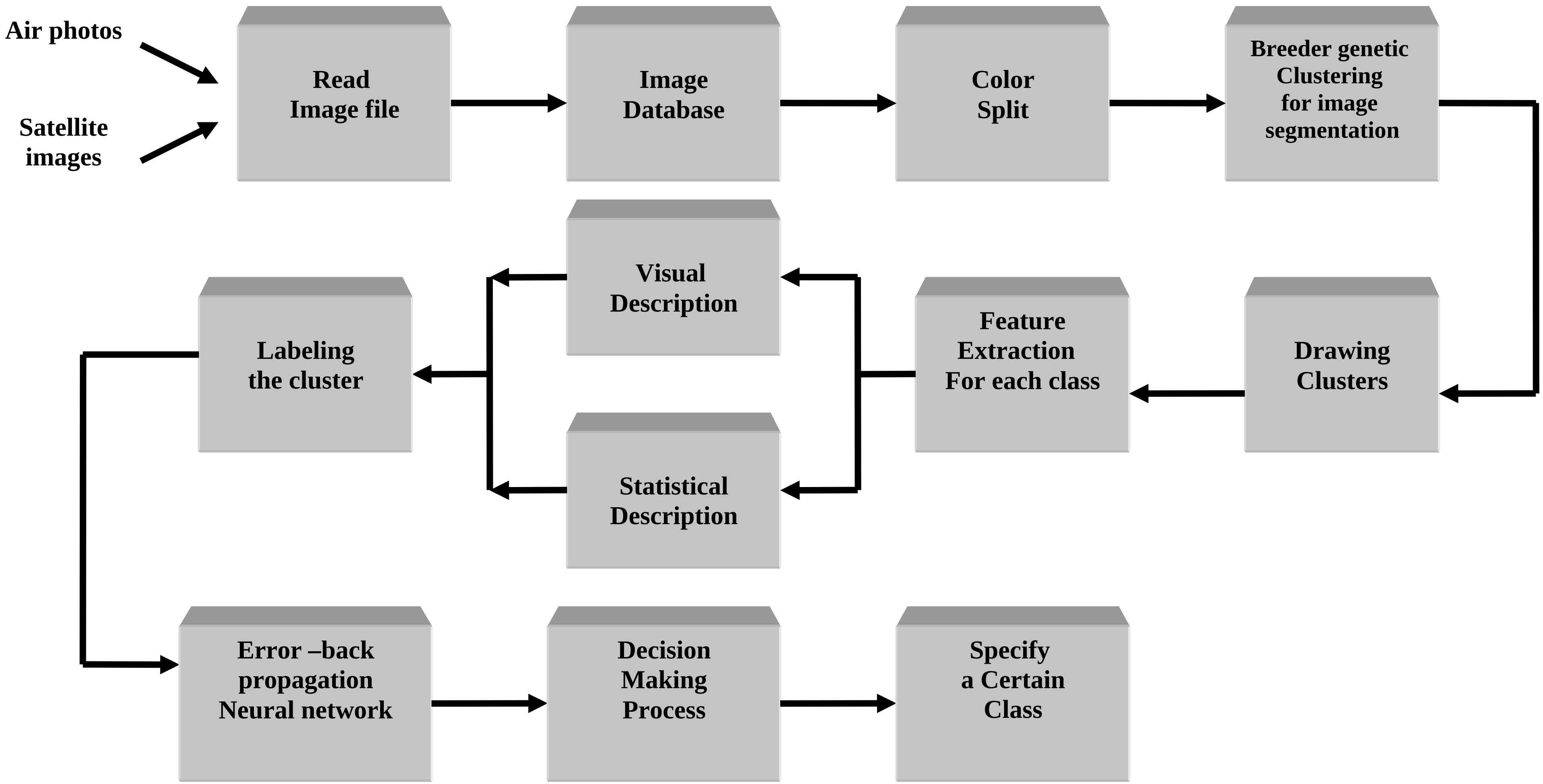


Figure (3-1) :A Block Diagram of Proposed System

3-2 Proposed System Stages

3-2-1 Read Image File

In this stage image acquisition that require classification their objects by proposed system that can be performed by using one of the remote sensing devices such as satellite or camera carried by air-planes .

These images usually consist of seven bands as explained in Chapter Two, paragraph (2-2-1). While in this work, the visible bands have been studied. Visible bands are represented by(red , green and blue portions of the electromagnetic spectrum). After separating the bands, we need to read image file to procedure processing operators on it and read image file process depending on image file format .

There are several types of image file format such as(PCX, JPEG, TIF, IMG, BMP). The bitmap(BMP)file format was chosen in the current study because of its popularity since the BMP file format is the standard format for storing bitmap images in a device-independent bitmap format so that gives the possibility to any windows application software to display the bitmap image file format on any type of display device(i.e., the bitmap specifies the pixel color in a form independent of the method used by the display device to represent color). The BMP files consist of three parts:-

i. Header part

The header contains information about the image such as the image size, number of color in source image. The size of header is 54 bytes and the information header gives the characteristics of the image as the dimension of the image file in pixels, type of compression algorithm used, and another information about image.

ii. Color palette part

The color palette part represents the palette of the image in which color is associated with each pixel(i.e., color palette represents the contrast of bias color, red, green and blue), the size of this part depends on the number of bits assignment of each image element (e.g.,1,2,8,16,24 bits)In this work each pixel is represented by three bytes which are interpreted as an RGB value. The first byte is blue component, the second green, and the third red. (24-bits)RGB model allows for $(2^8)^3 =$16.777.216 different colors.

iii. Image data part

This part contains the color value of each picture element(pixel). Bitmap image data in BMP file is stored in contiguous order lines. It is probably not surprising that they are stored in inverse order in which they are to be displayed, that is, the first line is to be read from the file in the bottom line of the image, and so on(i.e., the first pixel of the array represents the pixel in the lower left corner of the bitmap and last byte in the pixel in the upper right corner).

3-2-2 Image Database

According to the proposed system, one needs to describe each object in the image depending on their features (attributes), where digital images were segmented into different objects, which are labeled with appropriate category names. This stage can be performed by two methods, the first method describes each object depending on statistical calculation and the second method depends on visual description in this work using both methods.

So far, five categories have been defined for the image description. These categories are necessary for describing an image scene. The definition of these categories are given database (has five attributes and five different objects) as shown in Table (3-1), and the encoding values of the given database as shown in Table(3-2), in this table we use the binary values(0,1)to encoded the visual attributes.

Table(3-1):Explain image database

Object	Pattern	Shadow	Texture	Shape	Associative
Urban	Uniform	Yes	Rough	Known , Unknown	School, Road, Playgrounds
Road	Non-uniform	No	Rough	Unknown	Car
Forest	Non-uniform	Yes	Rough	Unknown	Water ,Vegetation
River	Near-uniform	No	Smooth	Unknown	Vegetation, Bridges
Football-Stadium	Uniform	Yes	Rough	Known	Scrolls, Car-attitude

Table (3-2):Encoding image database

Object No.	Pattern			Shadow		Texture		Shape		Associative								
	U	Near	Non	Yes	No	Smooth	Rough	Known	unknown	S	R	P	C	W	V	B	SC	CA
1	1	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0
1	1	0	0	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0
1	1	0	0	1	0	0	1	1	0	0	0	1	0	0	0	0	0	0
1	1	0	0	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0
1	1	0	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0
1	1	0	0	1	0	0	1	0	1	0	0	1	0	0	0	0	0	0
2	0	0	1	0	1	0	1	0	1	0	0	0	1	0	0	0	0	0
3	0	0	1	1	0	0	1	0	1	0	0	0	0	1	0	0	0	0
3	0	0	1	1	0	0	1	0	1	0	0	0	0	0	1	0	0	0
4	0	1	0	0	1	1	0	0	1	0	0	0	0	0	1	0	0	0
4	0	1	0	0	1	1	0	0	1	0	0	0	0	0	0	1	0	0
5	1	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	1	0
5	1	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	1

Where

Pattern :

U=uniform, Near=near-uniform ,Non=non-uniform

Associative :

S=school ,R=road, P=playgrounds,

C=car ,w=water ,V=vegetation,

B=bridges, Sc=scrolls ,CA=car-attitude

3-2-3 Color Split Stage

Color split process is consider necessary in most application and this work deals with true color(red, green, blue)(i.e., natural color). The color image file consists of two parts: header part and data region part, where each pixel (element)in the image is represented by three byte characteristic colors(red , green, blue). Split process is achieved by reading each element in the image then saving three bytes for each element in three files .

3-2-4 Breeder Genetic Clustering for Image Segmentation

This depends on the definition of clustering technical that has been explained in chapter two, paragraph (2-3-2). We can conclude that the main aim of clustering is to organize a collection of data items into clusters, such that items within a cluster are more "similar" to each other than they are to items in the other clusters. This notion of similarity can be expressed in very different ways, according to the purpose of the study, to domain specific assumptions and to prior knowledge of the problem[40], and because in most real life situations the number of clusters in a dataset is not known a priori. The real challenge in this situation is to be able to automatically evolve a proper value of number of clusters as well as providing the appropriate clustering. In this article, we propose a BGA based clustering techniques which can automatically evolve the appropriate clustering of image data set .

The breeder genetic clustering technique is subsequently referred to as breeder genetic clustering for unknown number of clusters(k), where k denotes the number of clusters. A flowchart of the method is provided in Figure(3-2). The main benefit from using BGA is to find a number of clusters and to provide the best seed for each cluster.

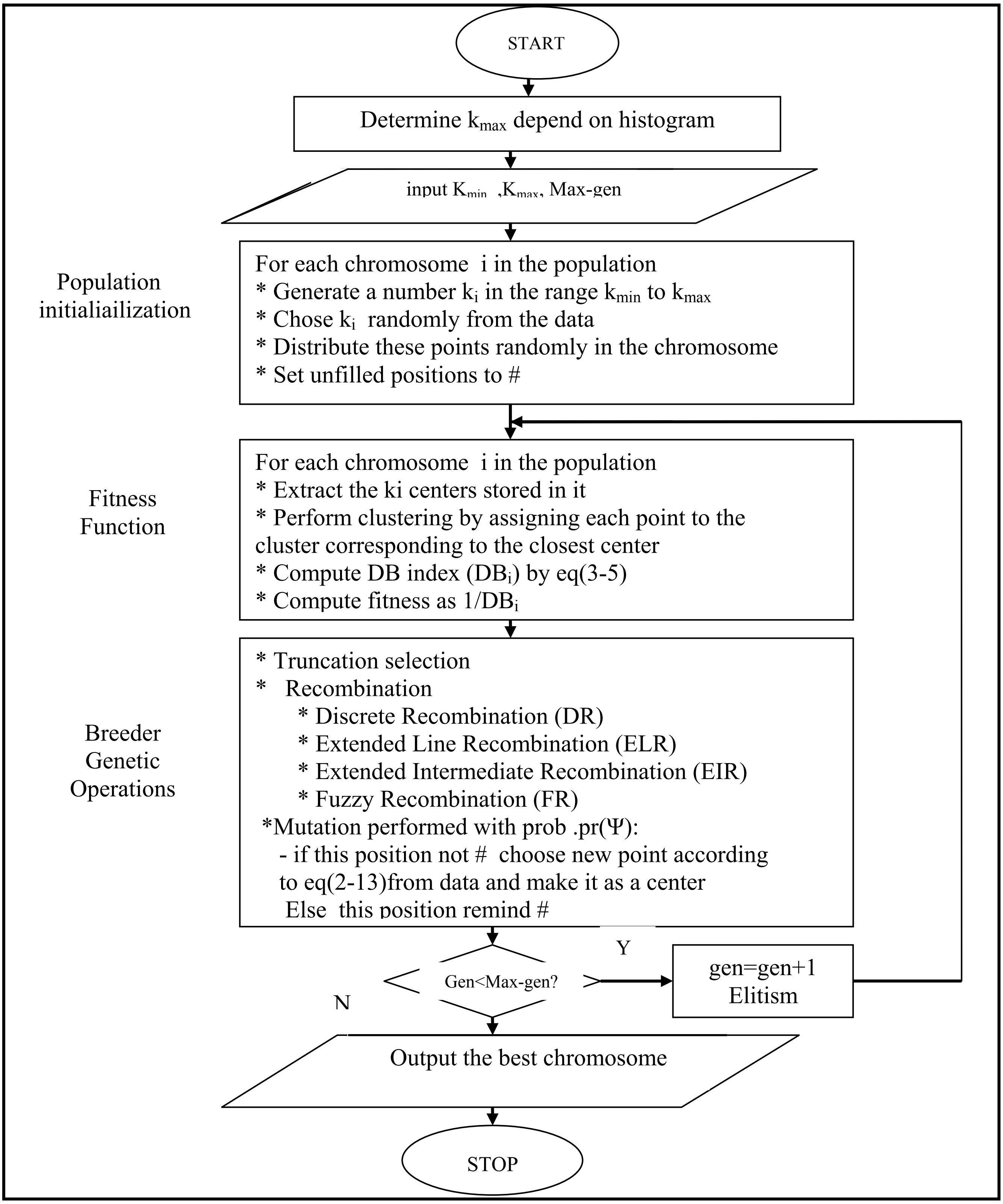


Figure (3-2) :Flowchart of Breeder Genetic Clustering for Image Segmentation

3-2-4-1 Representation of Solution

The chromosomes are make up of numbers(representing the coordinates of the centers drawing from image data set and bias components of color R,G,B) as well as the don't care symbol '#'. The value of K_i is assumed to lie in the range [K_{min}; K_{max}], where K_{min} is chosen to be 2 unless specified otherwise. The length of a string is taken to be K_{max}(i.e., K_{max} represents a number of higher peaks in image histogram) where each individual gene position represents either an actual center or a don't care symbol. The representation of actual center is shown in Figure(3-3).

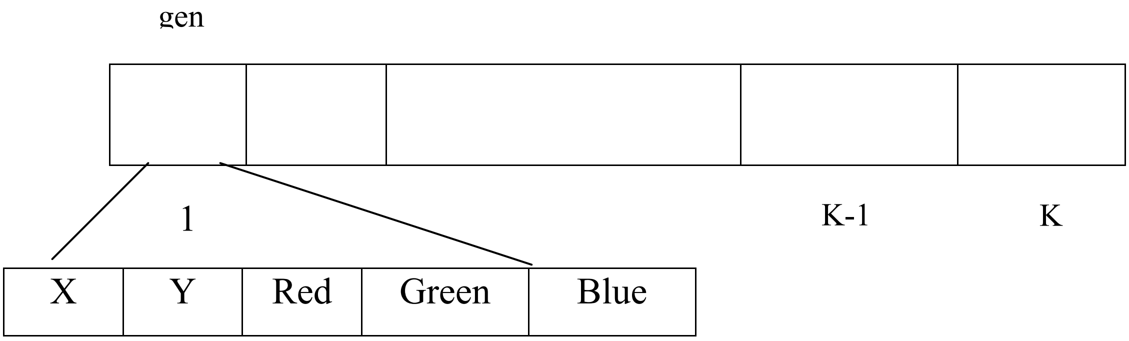


Figure (3-3): Representation of solution use in proposed system

3-2-4-2 Population Initialization

For each string i in the population (i=1,2,…., p, where p is the size of the population), a random number K_i in the range [K_{min}; K_{max}] is generated. This string is assumed to encode the centres of K_i clusters. For initializing these centres, K_i points are chosen randomly from the data set of image. These points are distributed randomly in the chromosome. Let us consider the following example.

<u>Example</u> :-Let K_{min} =2 and K_{max} =8. Let the random number K_i be equal to 3 for chromosome i. Then this chromosome will encode the centres of 3 clusters. Let the 3 cluster centres (3 randomly chosen points from the data set) be

(X_1,Y_1,R_1,G_1,B_1), (X_2,Y_2,R_2,G_2,B_2),(X_3,Y_3,R_3,G_3,B_3)
On random distribution of these centres in the chromosome, it may look like
(X_3,Y_3,R_3,G_3,B_3) # # (X_1,Y_1,R_1,G_1,B_1) # (X_2,Y_2,R_2,G_2,B_2)

3-2-4-3 Fitness Function [15],[22],[23],[41],[42]

The fitness of a chromosome is computed using the Davies–Bouldin index. This index is a function of the ratio of the sum of within-cluster scatter to between-cluster separation. The scatter within C_i , the ith cluster, is computed as

$$S_{i,q} = \left(\frac{1}{|C_i|} \sum_{x \in C_i} \{ ||x - z_i||_2^q \} \right)^{1/q}$$ ……………………(3-1)

where, z_i is the centroid of C_i , and is defined as

$$z_i = 1/n_i \sum_{x \in C_i} x$$ ……………………(3-2)

and n_i is the cardinality of C_i (i.e., the number of points in cluster C_i). The distance between cluster C_i and C_j is defined as(3-3)

$$d_{ij,t} = \left\{ \sum_{s=1}^{p} |z_{is} - z_{js}|^t \right\}^{1/t} = ||z_i - z_j||_t$$ ……………………(3-3)

Specifically, Si,q used in this article, is the average Euclidean distance of the vectors in class i to the centroid of class i. While dij,t is the Minkowski distance of order t between the centroids that characterize clusters i and j(i.e., in this work ,we use t=4). Subsequently we compute

$$R_{i,qt} = \max_{j, j \neq i} \left\{ \frac{S_{i,q} + S_{j,q}}{d_{ij,t}} \right\}$$ ……………………(3-4)

The Davies–Bouldin (DB) index is then defined as

$$DB = \frac{1}{K} \sum_{i=1}^{K} R_{i,qt}$$ ……………………(3-5)

The objective is to minimize the DB index for achieving proper clustering.

The fitness function for chromosome j is defined as 1/DBj, where DBj is the Davies–Bouldin index computed for this chromosome, where the maximization of the fitness function will ensure minimization of the DB index.

3-2-4-4 Breeder Genetic Operations

The following breeder genetic operations are performed on the population of strings for a number of generations.

i. Selection

The selection scheme in BGA is the truncation model in it, which starts from a population of p individuals. Only the T% elements showing the best fitness are chosen to give origin to the individuals of the next generation (Elitism). Usually truncation ratio lies in rang [10% to 50%].

Example :

Let p =100 and truncation ratio =50% then Elitism=100*50%=50 individuals .

ii. Recombination

During recombination each cluster centre is considered to be an indivisible gene. Four types of recombination process are discussed in this work(discrete recombination(DR), extended line recombination(ELR), extended intermediate recombination(EIR), fuzzy recombination(FR)), each of these methods produces one offspring after each recombination process. These methods are explained in the following:

1) When using Discrete Recombination (DR)
   a) Generated random number such as alpha
   b) Test if alpha bigger than or equal fixed number (pr)then child=parent1 else child=parent2. Figure (3-4) explains this method.

```
Algorithm :Discrete Recombination(DR)

For i= 1 to popsize
   For j=1 to k_max
      Select random number (alpha)
      If (alpha ≥ pr)then
          gen_j(child)= gen_j(parent1)
      else
          gen_j(child)= gen_j(parent2)
      end if
   end for
end for
```

Figure (3-4):Algorithm of Discrete Recombination

2)When using Extended Line Recombination (ELR)

a) Select random number(alpha)in the range [-d,1.0+d], where d is a parameter related to BGA, let d =0.25.
b) For each individual : test if the position of gene not '#' in parent1 and parent2 then go to step c else go to step d.
c) Test if fitness of parent2 is more than fitness of parent1 then the child is produced according to equation(2-7a) else apply equation(2-7b), go to e.
d) The position of gene in child is equal to '# '.
e) Test if the position of gene is not '#' in parent2 and '#' in parent1 then the position of gene in child is equal to the position of gene in parent2 else equal the position of gene in parent1. Figure (3-5) explains this method.

<u>Algorithm : Extended Line Recombination (ELR)</u>

```
Select alpha randomly in range[-d ,1.0+d]
For i=1 to popsize
   For j=1 to k_max
     If ((gen_j(parent1) < > '#') and (gen_j(parent2) < > '#')) then
     If ((fitness(parent2) ≥ fitness(parent1))then
         gen_j(child)= gen_j(parent1)+alpha*( gen_j(parent2)- gen_j(parent1))
     else
        gen_j(child)= gen_j(parent2)+alpha*( gen_j(parent1)- gen_j(parent2))
     end if
  else
     gen_j(child)= '#'
  end if
  If ((gen_j(parent1) = '#') and (gen_j(parent2) < > '#')) then
      gen_j(child)= gen_j(parent2)
  else
      gen_j(child)= gen_j(parent1)
  end if
 end for
end for
```

Figure (3-5):Algorithm of Extended Line Recombination

3) When using Extended Intermediate Recombination (EIR)

This method is different from(ELR)by selection a random number(alpha)for each individual in the population. Figure (3-6) explains this method.

```
Algorithm : Extended Intermediate Recombination (EIR)

For i=1 to popsize
    Select alpha_i randomly in range[-d ,1.0+d]
    For j=1 to k_max
        If ((gen_j(parent1) < > '#') and (gen_j(parent2) < > '#')) then
            If ((fitness(parent2) ≥ fitness(parent1))then
                gen_j(child)= gen_j(parent1)+alpha_i*( gen_j(parent2)- gen_j(parent1))
            else
                gen_j(child)= gen_j(parent2)+alpha_i*( gen_j(parent1)- gen_j(parent2))
            end if
        else
            gen_j(child)= '#'
        end if
        If ((gen_j(parent1) = '#') and (gen_j(parent2) < > '#')) then
            gen_j(child)= gen_j(parent2)
        else
            gen_j(child)= gen_j(parent1)
        end if
    end for
end for
```

Figure (3-6):Algorithm of Extended Intermediate Recombination

4) When using Fuzzy Recombination (FR)

In this method we use polynomial function as a membership function

$$\text{Membership function}= \frac{1}{\sqrt{2\pi}}\exp(-Z^2/2) \qquad \ldots\ldots\ldots\ldots\ldots\ldots(3\text{-}6)$$

a) Test if the position of gene not '#' in parent1 and parent2 then go to b else go to step e.
b) Find membership function of parent1 and parent2.
c) Test if membership function value of parent1 is bigger than the membership function of parent2 then: the position of gene in child is equal to the position of gene in parent1, else it's equal to the position of gene in parent2.

d) Test if the position of gene not '#' in parent1 and it's '#' in parent2 then : the position of gene in child is equal to the position of gene in parent1, else it's equal to the position of gene in parent2.

e) The position of gene in child is equal to '#'. Figure (3-7) explains this method

```
Algorithm : Fuzzy Recombination (FR)

For i=1 to popsize
  For j=1 to k_max
    If ((gen_j(parent1) < > '# ') and (gen_j(parent2) < > '#')) then
       msf_1=(1/(2*π)^(1/2))*exp(-1*(gen_j(parent1)^2)/2)
       msf_2=(1/(2*π)^(1/2))*exp(-1*(gen_j(parent2)^2)/2)
       If (msf_1  > msf_2)then
          gen_j(child)= gen_j(parent1)
       else
         gen_j(child)= gen_j(parent2)
       end if
       If ((gen_j(parent1) < > '#') and (gen_j(parent2) = '#')) then
          gen_j(child)= gen_j(parent1)
       else
          gen_j(child)= gen_j(parent2)
       end if
       gen_j(child)= '#'
    end if
  end for
end for
```

Figure (3-7):Algorithm of Fuzzy Recombination

iii. Mutation

Each position in a chromosome is mutated with probability $Pr(\Psi)=1/n$ so that, on average, one gene is mutated for each individual, as follows: If the position of gene is '#' then it remains '#' else it becomes new cluster center by applying the equation (2-13)in chapter two. Figure (3-8) explains it.

```
Algorithm : Mutation

For i=1 to popsize
   For j=1 to kmax
      select jwidth and jheight randomly in range[1, k], where k is parameter
      related to the machine accuracy .
      searchinterval1=(width*(width/2)*(2^(-jwidth))
      searchinterval2=(high*(height/2)*(2^(-jheight))
      if (genj(child)= '#') then
           genj(mchild)='#'
      else
          x= genj(child).x ± searchinterval1
          y= genj(child).y ± searchinterval2
          genj(mchild).x= x
          genj(mchild).y= y
          genj(mchild).r= rbmp(x ,y)
          genj(mchild).g= gbmp(x ,y)
          genj(mchild).b= bbmp(x ,y)
      end if
   end for
end for
```

Figure (3-8):Algorithm of Mutation

Where
mchild: child after mutation
rbmp : red bitmap file
gbmp : green bitmap file
bbmp : blue bitmap file

iv. Termination Criterion

We compute the on-line performance as termination criterion which has been explained in Chapter Two, use equation(2-16)to measure convergence rang of breeder genetic algorithm . See Figure(3-9).

<u>Algorithm : Termination Criterion</u>

```
Avgnew=0 , gen=1 , count=0 , sum=0
 Do
    Apply breeder genetic operations(selection ,recombination ,mutation ,
                                              validation ,evoluation)
     sum=sum +fitness(child)
     Avgnew=sum/gen
      If(|Avgnew – Avgold| ≤ const)then
         i=i+1
       else
         Avgold=Avgnew
       End if
       gen=gen+1
  loop until (gen ≥ max-gen & i < >countmax)
```

Figure (3-9):Algorithm of Termination Criterion

Where

Avgold : average fitness of producing children from gene number one to the actual gene.

Avgnew: average fitness of producing children from gene number one to the last gene.

Const : const value is determined depending on the problem type.

max-gen :the maximum number of generation number allowed.

v. Selection the Best Chromosome

The best string having the largest fitness(i.e., smallest Davies-Bouldin index value)see up the last generation provides the solution to the clusters count problem. We have up implanted elitism at each generation by preserving the best string see up to that generation in a location outside the population. Thus on termination, this location contains the centers of the final clusters that represent the image after clustering process and also provide a number of clusters.

3-2-5 Drawing Clusters

After selecting the best solution(chromosome)and finding the final clusters that represents image, return to spatial domain of image through representing each element(pixel)in image by special color of cluster center related to it. In this work , we use Mean Relative Error(MRE) measure of each picture element to measure the performance of clustering process .

$$MRE=\frac{\sum_{X=1}^{W}\sum_{Y=1}^{H}\frac{|f(x,y)-g(x,y)|}{f(x,y)}}{W*H} \quad \text{..................(3-7)}$$

where
W : width of image
H : height of image
f(x,y) :intensity of element(x,y)in original image .
g(x,y) :intensity of element(x,y)in image after clustering .

3-2-6 Features Extraction for each Class

In order to make an automated classification between different objects, some classifying features have to be extracted from the objects. In this part of this work we introduce two feature types, visual features and spectrum –based features.

3-2-6-1 Visual Description

Recognizing objects is the key to interpretation and information extraction. Observing the differences between objects and their backgrounds involves comparing different targets based on any, or all, of the visual elements of (shape, pattern, texture, shadow, and association). Visual interpretation using these elements is often a part of our daily lives, whether we are conscious of it or not. Identifying targets in remotely sensed images based on these visual elements allows us to further interpret and analyze. The nature of each of these interpretation elements is described below.

i. **Shape** refers to the general form, structure, or outline of individual objects. Shape can be a very distinctive clue for interpretation. Straight edge shapes typically represent urban or agricultural (field) targets, while natural features, such as forest edges, are generally more irregular in shape, except where man has created a road or clear cuts.

ii. **Pattern** refers to the spatial arrangement of visibly discernible objects. Typically an orderly repetition of similar tones and textures will produce a distinctive and ultimately recognizable pattern. Orchards with evenly spaced trees, and urban streets with regularly spaced houses are good examples of pattern.(i.e., each object can be described as uniform, near –uniform or non-uniform).

iii. **Texture** refers to the impression of "smoothness" or "roughness" of image features is caused by the frequency of change of tone in photographs. It is produced by a set of features too small to identify individually. Grass, cement, and water generally appear "smooth", while a forest canopy may appear "rough". Texture is one of the most important elements for distinguishing features in radar imagery.

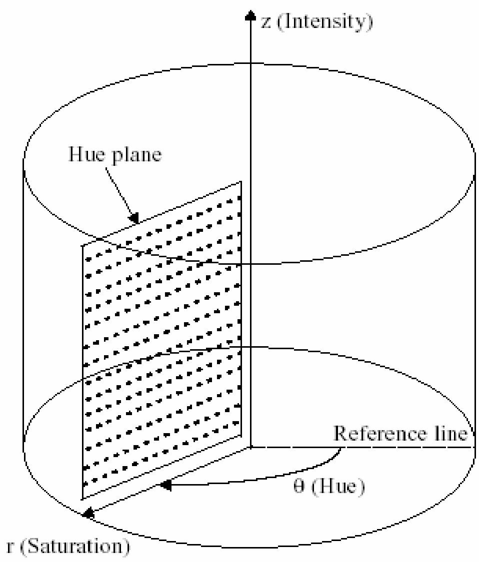
iv. **Shadow** is also helpful in interpretation as it may provide an idea of the profile and relative height of a target or targets which may make identification easier. However, shadows can also reduce or eliminate interpretation in their area of influence, since targets within shadows are much less (or not at all) discernible from their surroundings. electrical columns ,trees generally have shadow while roads and rivers do not have shadow.

v. **Association** takes into account the relationship between other recognizable objects or features in proximity to the target of interest. The identification of features that one would expect to associate with other features may provide information to facilitate identification. In the example given above, commercial properties may be associated with proximity to major transportation routes, whereas residential areas would be associated with schools, playgrounds, and sports fields. In our example, a lake is associated with boats and adjacent recreational land.

3-2-6-2 Features based on the spectrum

The light ,which is reflected by the object, forms a spectrum . The visible part of the spectrum of light is located between 400 and 700 um. Characterizations of the light is related to science of color. If the light is achromatic, its only attribute is intensity. The scalar measure of reflection is gray level . All colors are seen as variable combination of the three primary colors, red(R), green(G), and blue(B)[16] .

Combination of three primary colors is useful in spectrum measurement, when the visible part of the spectrum is considered. However to extract the spectrum information from the object, the consideration should be done in HSI(Hue, Saturation, Intensity)model. In the HSI-model hue(H) describes pure color in terms of the dominant wavelength (e.g., red, orange, yellow, ect.), whereas the saturation(S) gives the measure of degree to which a pure color is diluted by white light(e.g., pink is diluted red), intensity(I) is decoupled from the color information of the object [25][43][44]. HSI space can be considered as a cylinder as represented in Figure(3-10), where the coordinates *r*, q, and *z* are saturation, hue, and intensity, respectively.



Figure(3-10):HSI color space, and the cylinder

In this work we use hue, saturation and intensity information as following:-

$$H=COS^{-1}\left\{\frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}}\right\} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(3\text{-}8)$$

$$S=1-\frac{3*\min(R,G,B)}{(R+G+B)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(3\text{-}9)$$

$$I=\frac{1}{3}(R+G+B) \qquad \ldots\ldots\ldots\ldots\ldots\ldots(3\text{-}10)$$

3-2-7 Labeling the Cluster

According to the system design, one needs to determine a label for each cluster, and thus they are labeled with appropriate category name (i.e., one of the five categories described in Table(3-1)), this is called image object labeler(IOL),[45]. This stage can be achieved by procedure comparison process between the features that is found for each cluster and image database(i.e., The main benefit from this stage is to determined the desired output for each class).Then we use this information to train error back-propagation neural network.

3-2-8 Error back propagation neural network

After we get the number of clusters expected in the image dataset and the feature vectors that represent each cluster we can train error back-propagation neural network[45].

First, we need to determine the structure of network (i.e., number of nodes in input layer, number of nodes in hidden layer and number of nodes in output layer) and also the initial values of weights. Figure(3-11)show the structure of the artificial neural network.

Where a supervised ANN uses a set of training examples or records in this work, number of records equal to number of actual clusters result from breeder genetic clustering and number of attributes in each record equal to 21(i.e., visual and spectrum attributes) .

The output class vector c_j, (j=1,2,….,j), j is the number of different possible classes. If the output vector belongs to the $class_k$ then the element is equal to 1 while all the other elements in the vector are zeros. Therefore, the proposed number of output nodes in the output layer of ANN is j(i.e. in this work j=5).

The ANN is trained on the encoded vectors of the input attributes and the corresponding vectors of the output classes. The training of the ANN is processed until the convergence rate between the actual and the desired output will be achieved. The convergence rate can be improved by changing the number of epochs, the number of hidden nodes, the learning rate, and the momentum rate. Figure(3-12)shows the flowchart of learning process in error back-propagation algorithm.

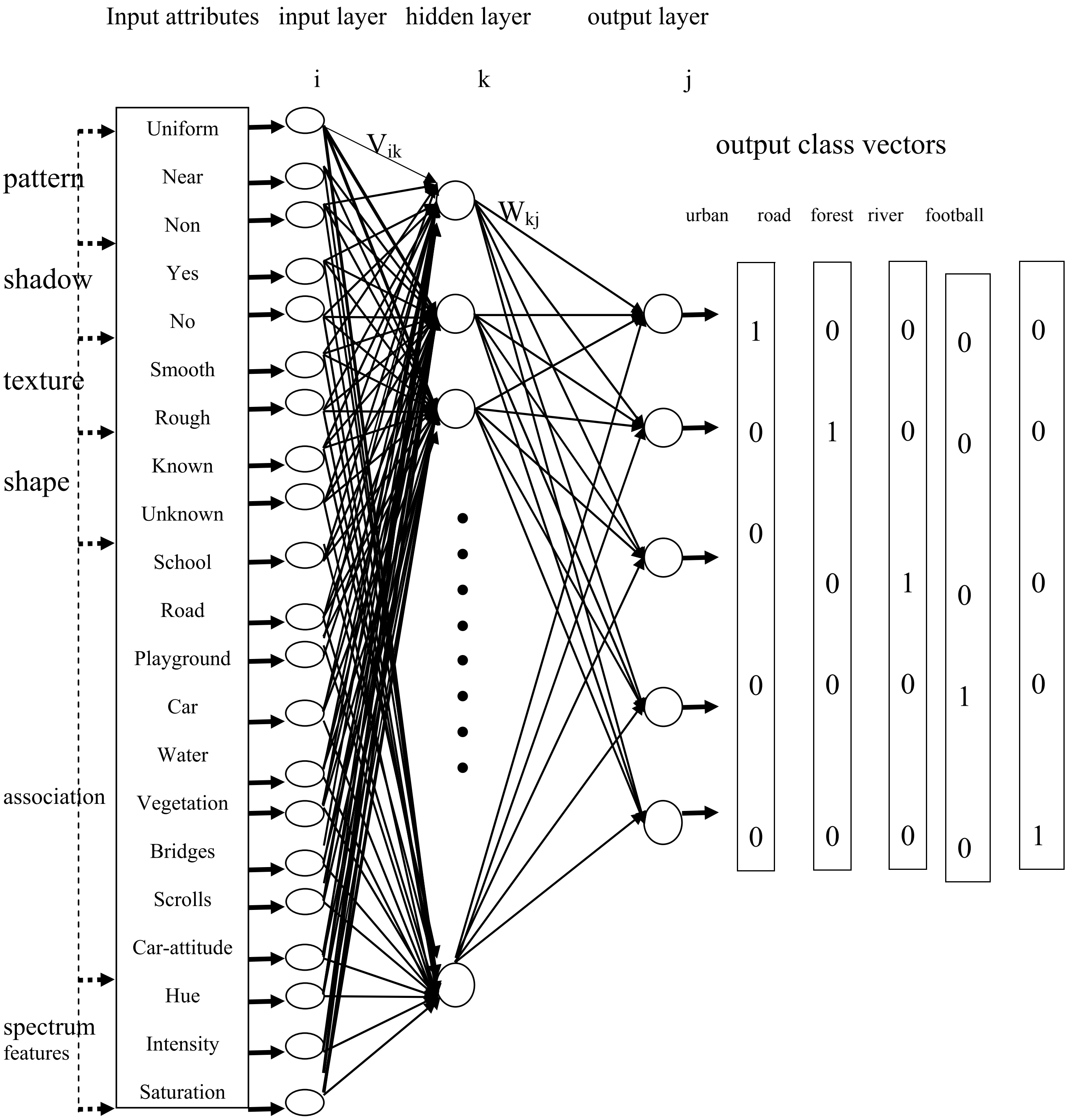


Figure (3-11):The Structure of the ANN

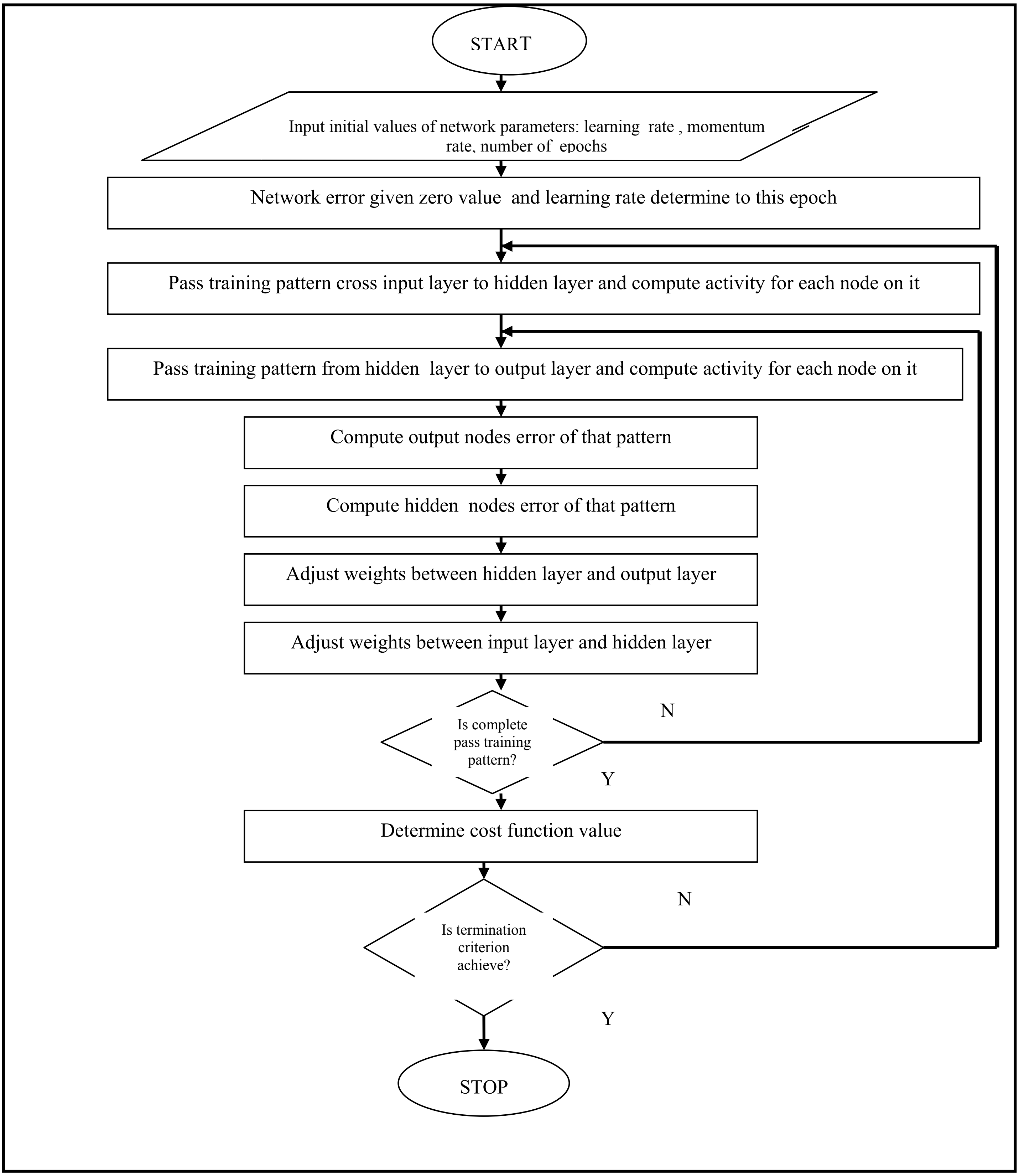


Figure (3-12) :Flowchart of Training Error back propagation algorithm

The following explain the learning steps that are shown in the above flowchart:-

Step1:-Input initial values to learning rate(η_0), maximum acceptable error to network (E_{max}), maximum number of epochs to learning network($E_{pochmax}$), momentum rate(α).

Step2:-Put network error value (MSE)equal to zero and current training pattern error equal to one and determine learning rate value to the current epoch according to equation(2-28), that explained in chapter two, paragraph(2-7-4).

Step3:-Compute hidden neurons activity by unipolar sigmoid function, with λ=1, according to equation(3-11)

$$h_k = f(\sum_{i=1}^{ns} s_i . v_{ik}) \qquad \text{.....................(3-11)}$$

where k=1,2,......,n_h .

step4:-The hidden neuron outputs become inputs to output neurons that apply the same sigmoid function to activity hidden. Compute output neuron activity according to (3-12).

$$o_j = f(\sum_{k=1}^{nh} h_k . w_{kj}) \qquad \text{.....................(3-12)}$$

where j=1,2,......,n_o .

step5:-Compute error signal value to output neurons of pattern p according to equation(3-13).

$$\delta_j = (d_j - o_j).\overline{f}(net_j) \qquad \text{.....................(3-13)}$$

we can find the derivative of function as follows:-

$$f(net_j) = \frac{1}{1 + \exp(-net_j)}$$

$$\bar{f}(net_j) = \frac{\exp(-net_j)}{[1+\exp(-net_j)]^2}$$

$$= \frac{1}{1+\exp(-net_j)} \cdot \frac{1+\exp(-net_j)-1}{1+\exp(-net_j)}$$

$$= \frac{1}{1+\exp(-net_j)}\left(\frac{1+\exp(-net_j)}{1+\exp(-net_j)} - \frac{1}{1+\exp(-net_j)}\right)$$

$$\bar{f}(net_j) = o_j.(1-o_j), \quad \text{where } j=1,2,\ldots,n_o, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3\text{-}14)$$

step6:- Compute error signal value in hidden neurons depended on output neurons error as in (3-15)

$$\delta_k = \sum_{j=1}^{no}\left(\delta_j.w_{kj}\right).\bar{f}\left(net_k\right), \quad \text{where } k=1,2,\ldots,n_h, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3\text{-}15)$$

$$\bar{f}(net_k) = h_k.(1-h_k) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3\text{-}16)$$

step7:- Adjust weights between hidden layer and output layer. To do this error back propagation algorithm use negative first derivative to cost function ratio to weight as follows[30],[34]:-

$$\Delta w_{kj} = -\eta_o.\frac{\partial E}{\partial w_{kj}}$$

$$= -\eta_o.\frac{\partial\left(0.5 * \sum_{j=1}^{no}\left(d_j - o_j\right)^2\right)}{\partial w_{kj}}, \quad o_j = f(net_j)$$

$$= -\eta_o.\frac{\partial\left(0.5 * \sum_{j=1}^{no}\left(d_j - f(net_j)\right)^2\right)}{\partial w_{kj}}, \quad net_j = \sum_{k=1}^{nh} w_{kj}.h_k$$

$$= \eta_0 .(d_j - o_j)\frac{\partial f(net_j)}{\partial w_{kj}}$$

$$= \eta_o .(d_j - o_j)\frac{\partial f(net_j)}{\partial net_j}.\frac{\partial net_j}{\partial w_{kj}}$$

$$= \eta_o .(d_j - o_j).\bar{f}(net_j).\frac{\partial net_j}{\partial w_{kj}}$$

$$= \eta_o .(d_j - o_j).\bar{f}(net_j).h_k$$

$$= \eta_o .\delta_j .h_k$$

The adjustment equations :-

$$\Delta w_{kj}^{(t+1)} = \eta.\delta_j.h_k + \alpha.\Delta w_{kj}^{(t)}, \qquad \text{…………………..(3-17a)}$$

$$w_{kj}^{(t+1)} = w_{kj}^{(t)} + \Delta w_{kj}^{(t+1)} \qquad \text{…………………..(3-17b)}$$

where

$k = 1,2,\ldots,n_h$ & $j=1,2,\ldots,n_o$,

α :-momentum rate

$\Delta w_{kj}^{(t)}$:-represent different between current weight and prior weight .

step8:-Adjust weights between input layer and hidden layer as follows:-

$$\Delta v_{ik} = -\eta_o .\frac{\partial E}{\partial V_{ik}}$$

$$= -\eta_o .\frac{\partial\left(0.5 * \sum_{j=1}^{no}\left(d_j - o_j\right)^2\right)}{\partial v_{ik}}$$

$$= \eta_o .\sum_{j=1}^{no} (d_j - o_j)\frac{\partial f(net_j)}{\partial v_{ik}}$$

$$= \eta_o .\sum_{j=1}^{no} (d_j - o_j)\frac{\partial f(net_j)}{\partial net_j}.\frac{\partial net_j}{\partial v_{ik}}$$

$$=\eta_o.\sum_{j=1}^{no} (d_j - o_j).\bar{f}\left(net_j\right).\frac{\partial net_j}{\partial v_{ik}}$$

$$=\eta_o.\sum_{j=1}^{no} \delta_j.\frac{\partial net_j}{\partial h_k}.\frac{\partial h_k}{\partial v_{ik}}$$

$$=\eta_o.\sum_{j=1}^{no} \delta_j.w_{kj}\frac{\partial h_k}{\partial net_k}.\frac{\partial net_k}{\partial v_{ik}}, \quad \text{where } net_k=\sum_{i=1}^{ns} v_{ik}.s_i$$

$$=\eta_o.\sum_{j=1}^{no} \delta_j.w_{kj}.\overline{f}(net_k).\frac{\partial net_k}{\partial v_{ik}}$$

$$=\eta_o.\sum_{j=1}^{no} \delta_j.w_{kj}.\overline{f}(net_k).s_i$$

$$=\eta_o.\sum_{j=1}^{no} \delta_j.w_{kj}.h_k(1-h_k).s_i, \quad \text{where } \bar{f}(net_k)=h_k.(1-h_k)$$

$$=\eta_o.\delta_k.s_i, \quad \text{where } \delta_k=\sum_{j=1}^{no}\left(\delta_j.w_{kj}\right).h_k(1-h_k)$$

The adjustment equations :-

$$\Delta v_{ik}^{(t+1)}=\eta_o.\delta_k.s_i+\alpha.\Delta v_{ik}^{(t)}, \qquad \text{.....................(3-18a)}$$

$$v_{ik}^{(t+1)}=v_{ik}^{(t)}+\Delta v_{ik}^{(t+1)} \qquad \text{.....................(3-18b)}$$

where

$k=1,2,\ldots,n_h$ & $i=1,2,\ldots,n_s$,

α :-momentum rate

$\Delta v_{ik}^{(t)}$:-represent different between current weight and prior weight .

step9:-Increase value p by one to input the next pattern in learning process, if it does not reach to maximum number to training patterns then return to step3 to training network on that pattern else transform to step10.

Step10:-After completing input to all training patterns to the network, compute cost function value that is represented by mean square error as in(3-19).

$$MSE = \frac{1}{2}\sum_{p=1}^{P}\sum_{j=1}^{no}\left(d_j^p - o_j^p\right)^2 \qquad \text{.....................(3-19)}$$

step11:- In this step, the termination criterion is tested. This condition is valid if the total error value of network becomes less than the expected error of it (E_{max}), or the current Epoch value(t) is bigger than maximum number of learning epochs ($E_{pochmax}$). Else return to step 2.

3-2-9 Decision Making Process

After verification of one of the stopping criterion to error back propagation algorithm such as verified cost function condition or exceeding the number of epochs to maximum number of learning epochs without reaching network error to a value less than the required value, we can say that the error –back propagation is complete there work.

If cost function condition is verified this means network can train itself on input pattern to it and recognizing this pattern (i.e., the network successful in training process). While if the second condition verified (i.e., the network does not reach to an acceptable error and exceeds number of epochs) this means the network fails in the training process and recognition the input pattern.

3-2-10 Specify a Certain Class

There are several methods to specify a certain class. One of these methods depends on use IF-Then Rule, such as images are described in terms of many characteristics and a rule is given which specifies the attributes that determine membership of the target class[2][46][47][48]. The resultant of testing each image is add to image database to extended it.

This rule takes the following format:-

IF _Condition_ Then_ Action

Example:-
The following two rules that determine the membership of football-stadium class in the image database are shown in Table (3-3).

Table (3-3):Two rules satisfy the football-stadium class

Rule NO.	Rule
1	IF pattern is uniform and shadow is yes and texture is rough and shape is known and associative is scrolls Then class football-stadium.
2	IF pattern is uniform and shadow is yes and texture is rough and shape is known and associative is car -attitude Then class football-stadium.

Chapter Four

Case Study

4-1 Introduction

To test the performance of DSCOAPSI that is built depending on using soft computing techniques as explained in the prior chapter, we use some of images that have different types of objects as implementation examples to explain behavioral of that system. we getting about these images by using internet sites.

Before running the system of each images, the system must have collect some important prior information for it. This information can be used when some parameters need to enter the system such as finding , determine description for each object that the system want classification.

Three cases study are used to test the DSCOAPSI and the results of each case are explained below.

4-2 Case Study 1: Test Image for Baghdad Area

Figure(4-1) : Image for Baghdad City

4-2-1 A Sample of Image Data for the Experiment

A System Pour l'Observation de la Terre (SPOT) satellite image of Baghdad , Iraq was used for the classification. The SPOT image has 3 spectral bands sensing the red, green and blue portions of the electromagnetic spectrum. Urban, vegetation, roads and rivers were recorded during a ground reference survey. From the SPOT image, a minimum number of object in this image equals to Four. Typically, remote sensing data provides a large number of examples for each class. Total number of pixels in image (40000) pixel .

4-2-2 Result of Test:-

Step1:- Find the maximum number of clusters existing in that image by drawing a histogram of image and calculate the highest peaks in the histogram (i.e., every pixel is consider a peak if it has 0.011 iteration from total number of pixels). Then split colors and find the histogram for each band. See Figure(4-2) .

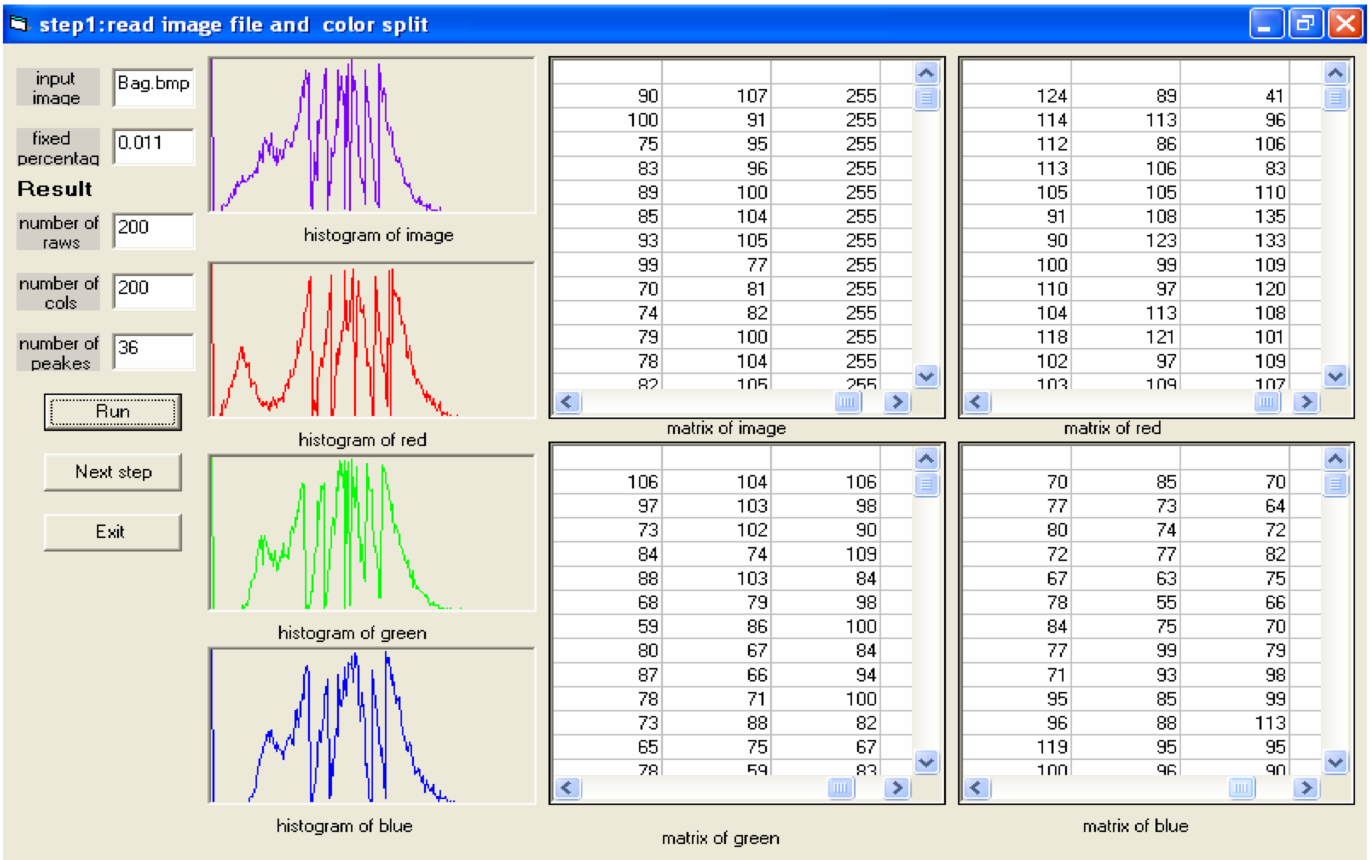
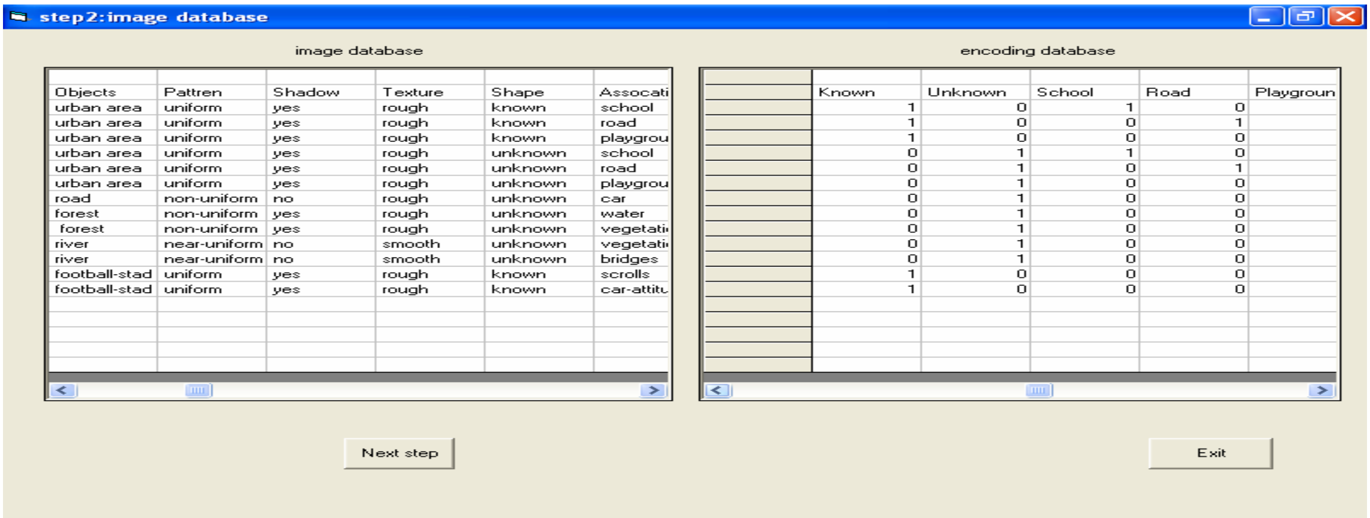


Figure (4-2) : Read the Image File and Color Split to Image for Baghdad City

Step2 :- Building database that describes each object in image for more detail see appendix and the visual features of this objects are encoded by using binary number(0,1). See Figure(4-3).



Objects	Pattren	Shadow	Texture	Shape	Assocati
urban area	uniform	yes	rough	known	school
urban area	uniform	yes	rough	known	road
urban area	uniform	yes	rough	known	playgrou
urban area	uniform	yes	rough	unknown	school
urban area	uniform	yes	rough	unknown	road
urban area	uniform	yes	rough	unknown	playgrou
road	non-uniform	no	rough	unknown	car
forest	non-uniform	yes	rough	unknown	water
forest	non-uniform	yes	rough	unknown	vegetati
river	near-uniform	no	smooth	unknown	vegetati
river	near-uniform	no	smooth	unknown	bridges
football-stad	uniform	yes	rough	known	scrolls
football-stad	uniform	yes	rough	known	car-attitu

Known	Unknown	School	Road	Playgroun
1	0	1	0	
1	0	0	1	
1	0	0	0	
0	1	1	0	
0	1	0	1	
0	1	0	0	
0	1	0	0	
0	1	0	0	
0	1	0	0	
0	1	0	0	
0	1	0	0	
1	0	0	0	
1	0	0	0	

Figure (4-3) : Image Database for Baghdad City

Step3 :- Apply breeder genetic clustering algorithm to find the actual number of clusters existing in that image data set (i.e. find best seed for each cluster and number of pixels found in that cluster) . Before this, we need to determine some of parameters relate to BGA such as population size, minimum number of clusters, truncation rate, and the recombinationmethod(DR,ELR,EIR,FR).Seefigure(4-4).

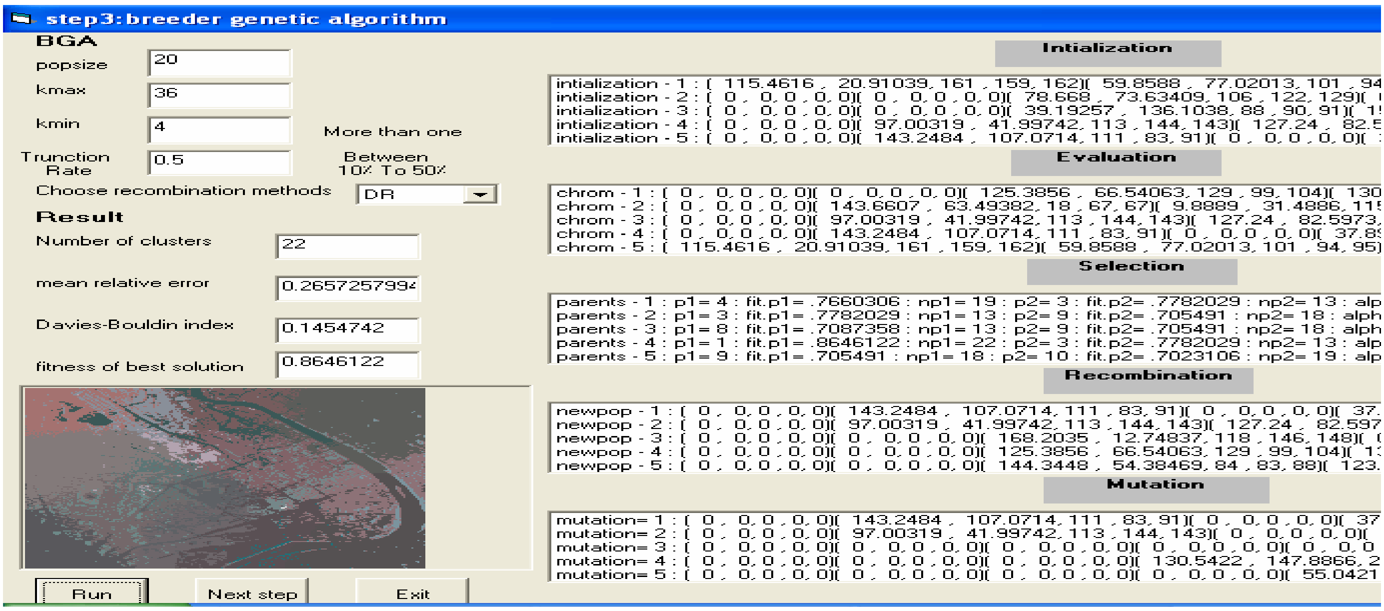


Figure (4-4) : Result of Breeder Genetic Algorithm by using Discrete Recombination

Table (4-1): Actual and computed values for the data sets of case study one

Cluster NO.	Center coordinates		Number Of pixels
	Actual	Compute	
3	(125.3,66.5,129,99,104)	(125.3,66.5,129,99,104)	2332
4	(130.5,147.8,29,115,123)	(130.5,147.8,29,115,123)	222
6	(80.9,122,1,109,102,106)	(80.9,122,1,109,102,106)	2171
7	(118.3,136.6,90,80,84)	(118.3,136.6,90,80,84)	3462
9	(162.2,154.2,85,81,82)	(162.2,154.2,85,81,82)	4858
10	(28.5,9.4,164,114,112)	(28.5,9.4,164,114,112)	1698
11	(136.8,81.0,116,135,137)	(136.8,81.0,116,135,137)	973
12	(2.5,156.9,89,88,92)	(2.5,156.9,89,88,92)	3319
13	(47.8,118.9,109,137,136)	(47.8,118.9,109,137,136)	671
14	(65.6,195.9,255,255,255)	(65.6,195.9,255,255,255)	1002
15	(52.6,14.3,137,143,153)	(52.6,14.3,137,143,153)	1250
18	(115.3,12.8,118,92,93)	(115.3,12.8,118,92,93)	1534
19	(69.3,103.0,92,118,118)	(69.3,103.0,92,118,118)	653
20	(146.1,25.5,92,93,90)	(146.1,25.5,92,93,90)	4226
21	(105.7,27.6,59,88,87)	(105.7,27.6,59,88,87)	1542
24	(73.5,109.7,112,107,108)	(73.5,109.7,112,107,108)	600
25	(169.0,103.9,141,114,119)	(169.0,103.9,141,114,119	2061
26	(54.3,115.4,116,104,106)	(54.3,115.4,116,104,106)	1776
29	(196.7,105.3,123,148,158)	(196.7,105.3,123,148,158)	362
32	(85.1,119.3,94,97,101)	(85.1,119.3,94,97,101)	1301
34	(60.5,45.9,179,163,176)	(60.5,45.9,179,163,176)	365
35	(38.6,84.0,131,122,122)	(38.6,84.0,131,122,122)	3622

Total number of pixels=40000

Total number of clusters=36

Number of actual clusters=22

Step4 :- Draw each cluster and calculate features for each one. Example of this we now explain the features of cluster number three . See Figure(4-5).

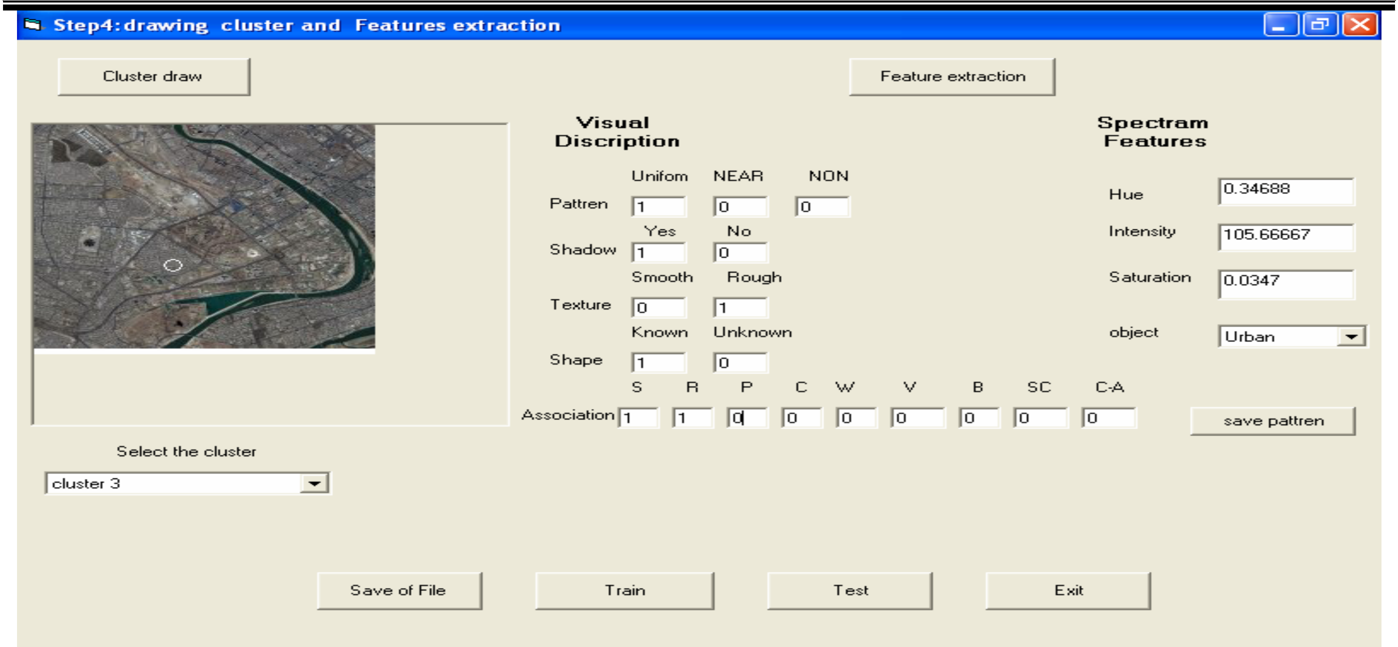


Figure (4-5) : Features of Cluster Number Three of Baghdad Area

Step5:- Compare the features for each cluster with image database to label that clusters. By applying the above step for each cluster in Baghdad image, we can obtain the following results.

- Three clusters labeled as river.
- Twelve clusters labeled as urban area.
- Five clusters labeled as roads.
- Two clusters labeled as forest.

Step6:-Train back propagation neural network on the feature vectors for each cluster to determine the correct class for each feature vector. Before this, we need to determine some of parameters related to BPNN .

Parameters:

Maximum number of epochs=10000.

Learning rate=0. 7

Momentum rate=0.01

Maximum value of acceptable error =0.09

Result: The network enables from classification of all image objects with MSR=8.99999579769739E-02, after(7904) epoch. See Figure(4-6).

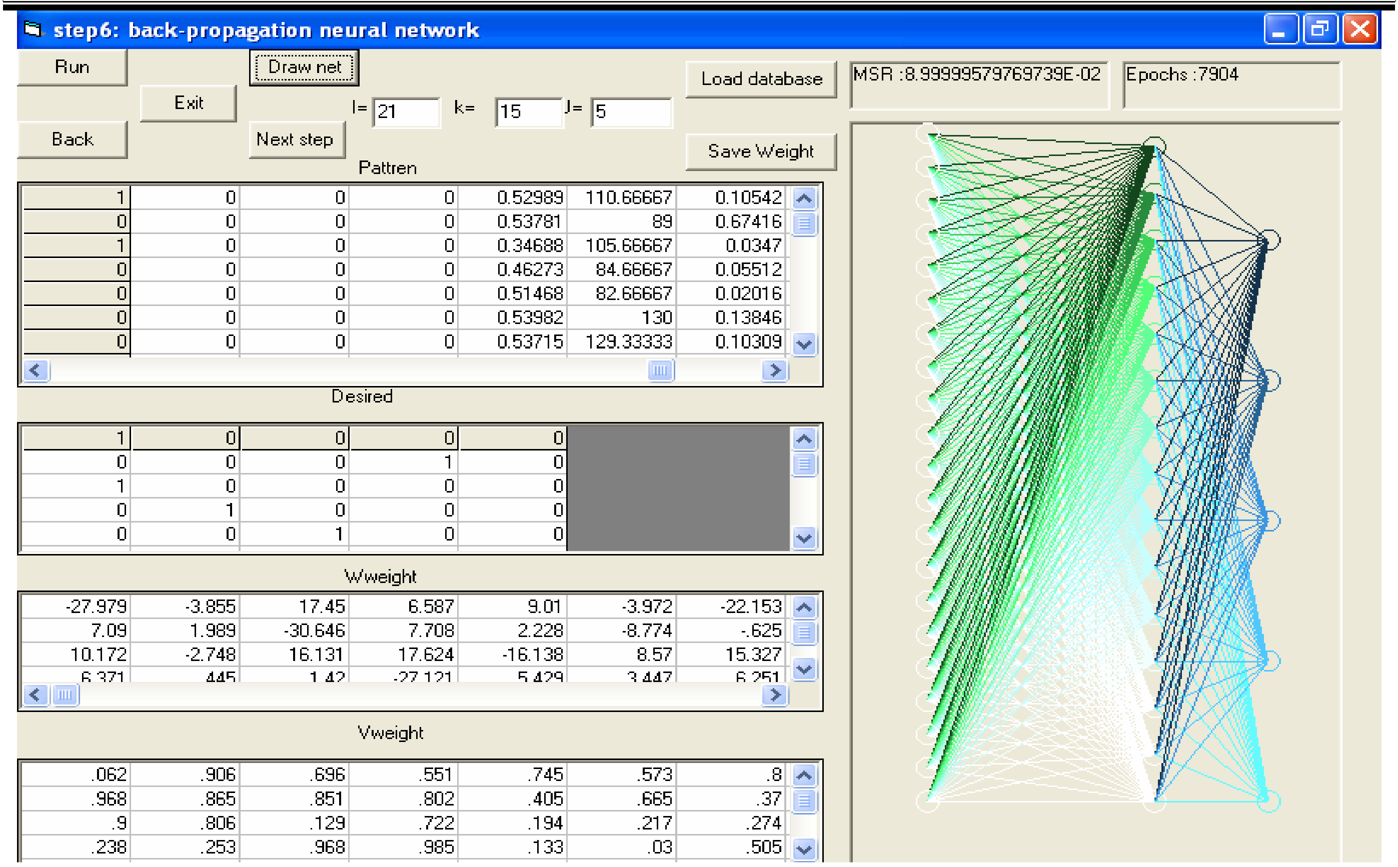


Figure (4-6) : Result of Back Propagation Neural Network for Case Study One

Step7:- Use IF-Then Rule to form several rules that govern each class attributes . This step makes the system more precise, as follows:-

IF (hue=[-0.89429 ,0.54728])and(saturation=[0.01835,1])
and(intensity=[89.66667,172.66667])and(pattern_uniform=1)
and(pattern_near_uniform=0)and(pattern_non_uniform=1)
and(shape_known=1)or(shape_unknown=1)and(texture_smooth=0)
and(texture_rough=1)and(shadow_yes=1)and(shadow_no=0)
and(associative_school=1)or(associative_road=1)or(associative_playground=1)
and(associative_car=0) and(associative_water=0) and(associative_vegetation=0)
and(associative_bridges=0) and(associative_scrolls=0) and(associative_car_attitude=0)
Then class Urban area.

IF(hue=[-0.46273,0.53991])and(saturation=[0.04294,1])and(intensity=[78,130])and (pattern_uniform=0) and(pattern_near_uniform=0)and(pattern_non_uniform=1) and(shape_known=0)and(shape_unknown=1)and(texture_smooth=0) and(texture_rough=1)and(shadow_yes=0)and(shadow_no=1) and(associative_school=0) and(associative_road=0)and(associative_playground=0) and(associative_car=1) and(associative_water=0) and(associative_vegetation=0) and(associative_bridges=0) and(associative_scrolls=0) and(associative_car_attitude=0) Then class Road.

IF (hue=[0,0.51468])and(saturation=[0.02016,1])and(intensity=[82.66667,255])and (pattern_uniform=0)and(pattern_near_uniform=0)and(pattern_non_uniform=1) and(shape_known=0)and(shape_unknown=1)and(texture_smooth=0)and (texture_rough=1)and(shadow_yes=1) and(shadow_no=0)and(associative_school=0) and(associative_road=0) and(associative_playground=0) and(associative_car=0) and(associative_water=1)or(associative_vegetation=1)and(associative_bridges=0) and(associative_scrolls=0) and(associative_car_attitude=0) Then class Forest.

IF(hue=[0.50550,0.53982])and(saturation=[0.08911, 0.67416]) and(intensity=[89, 143])and(pattern_uniform=0)and(pattern_near_uniform=1) and(pattern_non_uniform=0)and(shape_known=0)and(shape_unknown=1) and(texture_smooth=1)and(texture_rough=0)and(shadow_yes=0) and(shadow_no=1)and(associative_school=0) and(associative_road=0) and(associative_playground=0) and(associative_car=0) and(associative_water=0) and(associative_vegetation=1) and(associative_bridges=0) and(associative_scrolls=0) and(associative_car_attitude=0) Then class River.

4-3 Case Study 2: Test Image for Otago Area

Figure (4-7) : Image for Otago City

4-3-1 A Sample of Image Data for the Experiment

A System Pour l'Observation de la Terre (SPOT) satellite image of the Otago, Dunedin, New Zealand, was used for the classification. The SPOT image has 3 spectral bands sensing the red, green and blue portions of the electromagnetic spectrum containing urban, vegetation , roads and football-stadium , were recorded during a ground reference survey. From the SPOT image, a minimum number of objects in this image equal to 17 .Typically, remote sensing data provides a large number of examples for each class and this image is considered very complex because it contain more details. Total number of pixels in image (71824)pixel .

4-3-2 Result of Test:-

Step1:- Find the maximum number of clusters existing in that image by drawing histogram of image and calculate the highest peaks in histogram(i.e., every pixel is considered a peak if it has 0.006 iteration from total number of pixels). Then split colors and find histogram for each band. See Figure(4-8).

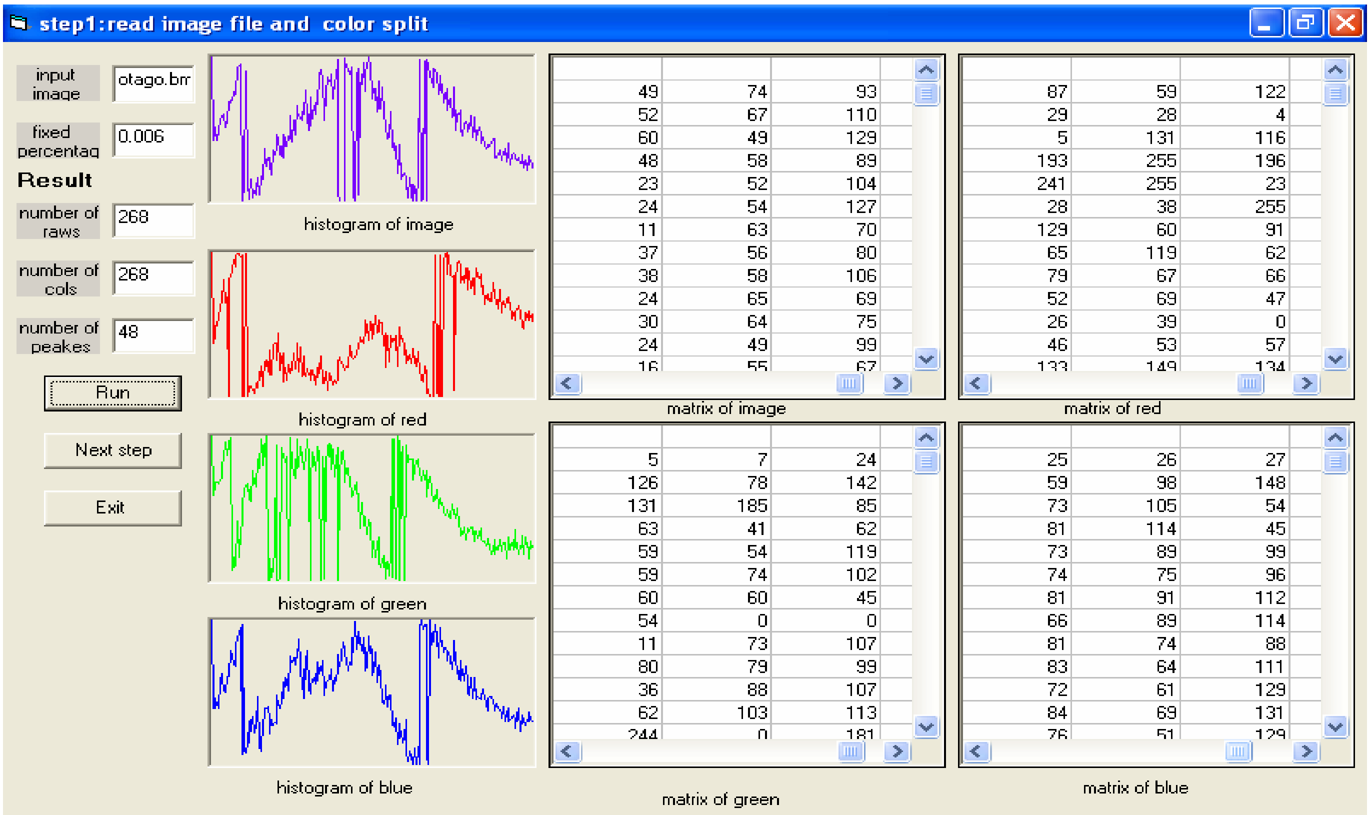


Figure (4-8) : Read the Image File and Color Split to Image for Otago City

Step2 :- Build database that describes each object in image for more detail see appendix and the visual features of this objects are encoded by using binary number(0,1). See Figure(4-9).

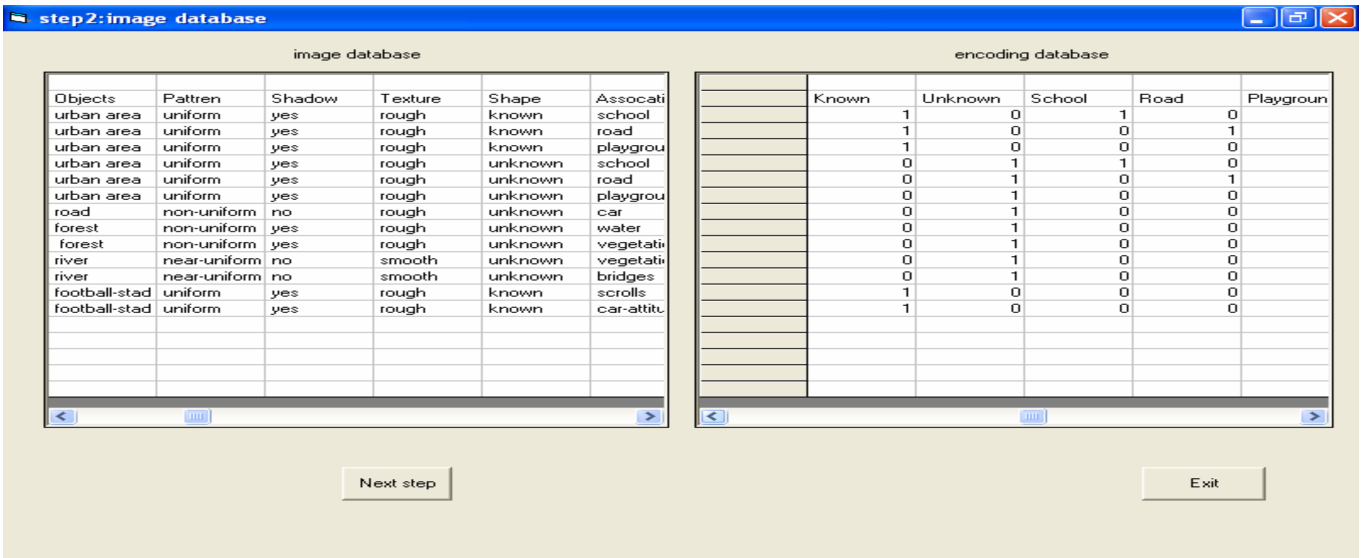


Figure (4-9) : Image database for Otago City

Step3 :- Apply breeder genetic clustering algorithm to find the actual number of clusters existing in that image data set (i.e. find best seed for each cluster and number of pixels found in that cluster). Before this, we need to determine some of parameters relate to BGA such as population size, minimum number of clusters, truncation rate, and the recombination method (DR,ELR,EIR,FR). See Figure(4-10).

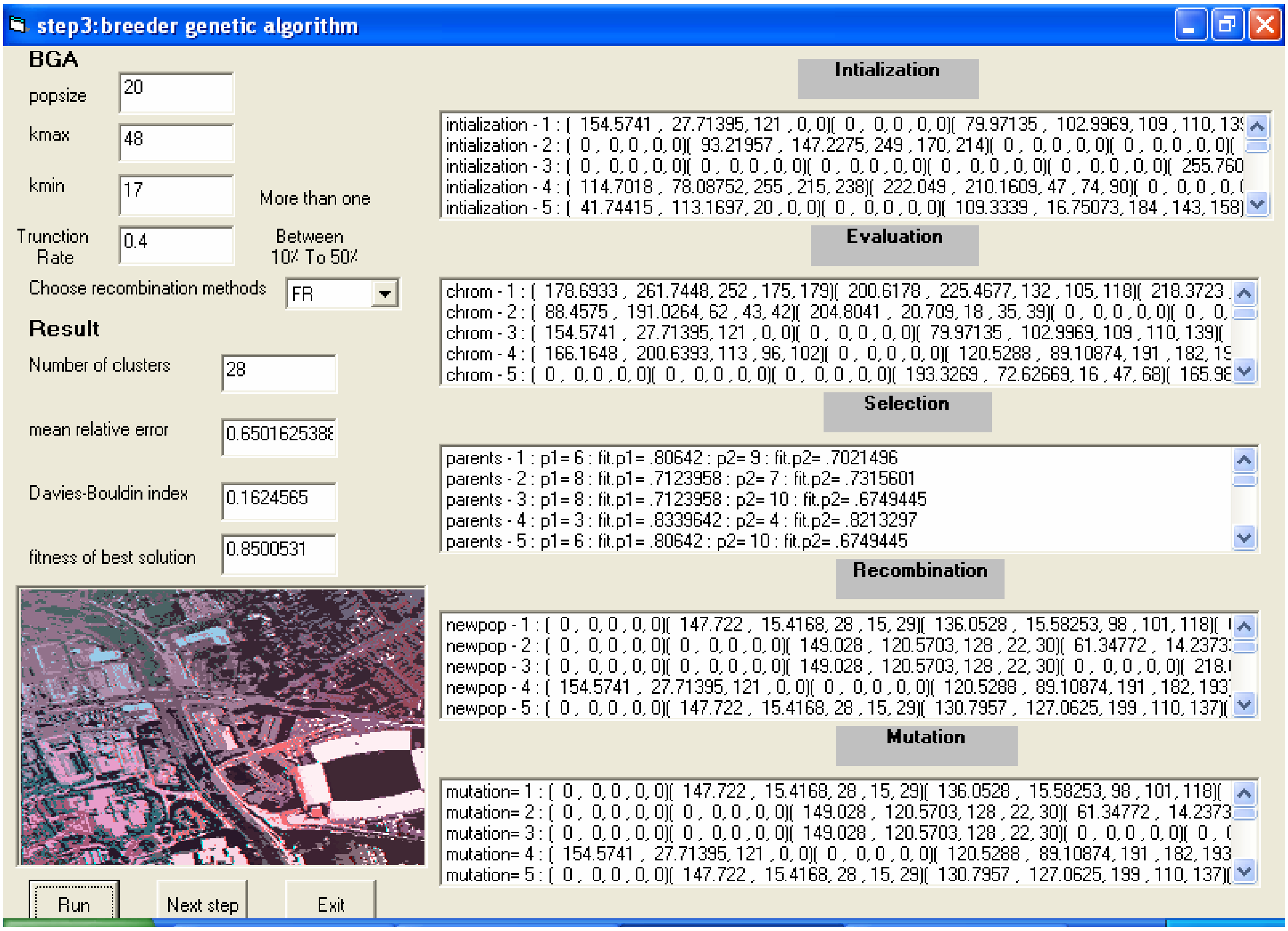


Figure (4-10) : Result of Breeder Genetic Algorithm by using Fuzzy Recombination

Table (4-2): Actual and computed values for the data sets of case study two

Cluster NO.	Center coordinates		Number Of pixels
	Actual	Compute	
1	(178.6,261.7,252,175,179)	(178.6,261.7,252,175,179)	889
2	(200.6,225.4,132,105,118)	(200.6,225.4,132,105,118)	5489
3	(218.3,126.4,64,40,52)	(218.3,126.4,64,40,52)	4726
4	(167.5,135.1,61,34,50)	(167.5,135.1,61,34,50)	2554
5	(209.3,12.7,109,101,123)	(209.3,12.7,109,101,123)	1990
6	(117.3,221.1,107,98,111)	(117.3,221.1,107,98,111)	4713
7	(41.1,73.0,158,147,175)	(41.1,73.0,158,147,175)	1066
8	(243.0,99.6,255,239,243)	(243.0,99.6,255,239,243)	2757
11	(136.1,166.4,248,213,229)	(136.1,166.4,248,213,229)	2492
12	(15.0,209.3,170,89,120)	(15.0,209.3,170,89,120)	2707
13	(225.8,57.1,152,73,90)	(225.8,57.1,152,73,90)	2025
15	(113.4,138.3,41,24,42)	(113.4,138.3,41,24,42)	4013
16	(114.1,198.9,0,255,255)	(114.1,198.9,0,255,255)	303
19	(93.7,11.6,74,99,100)	(93.7,11.6,74,99,100)	2153
20	(212.3,216.1,112,0,0)	(212.3,216.1,112,0,0)	1919
27	(101.5,40.2,117,89,110)	(101.5,40.2,117,89,110)	3291
28	(206.3,79.4,145,96,131)	(206.3,79.4,145,96,131)	2283
30	(27.7,252.7,64,41,46)	(27.7,252.7,64,41,46)	3175
31	(123.9,77.3,161,125,152)	(123.9,77.3,161,125,152)	3014
32	(156.7,16.7,56,37,51)	(156.7,16.7,56,37,51)	4820
34	(48.9,47.6,176,143,171)	(48.9,47.6,176,143,171)	1168
36	(59.8,57.1,151,204,233)	(59.8,57.1,151,204,233)	900
40	(44.7,134.2,232,157,202)	(44.7,134.2,232,157,202)	2269
41	(16.7,41.3,146,114,139)	(16.7,41.3,146,114,139)	2810
42	(16.0,240.5,178,102,125)	(16.0,240.5,178,102,125)	1630
43	(132.7,109.7,247,108,116)	(132.7,109.7,247,108,116)	1687
45	(68.0,148.9.48,110,122)	(68.0,148.9.48,110,122)	2706
47	(186.5,237.3,84,97,114)	(186.5,237.3,84,97,114)	2275

Total number of pixels=71824

Total number of clusters=48

Number of actual cluster=28

Step4 :- Draw each cluster and calculate features for each one. Example of this we now explain the features of cluster number three. See Figure(4-11).

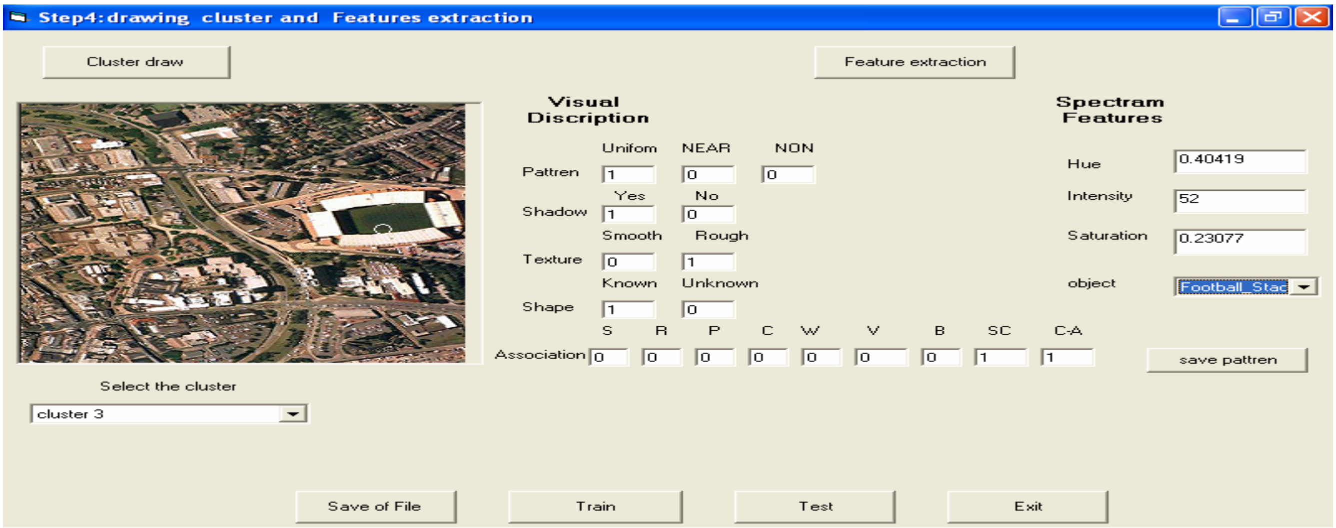


Figure (4-11) : Features of Cluster Number Three of Otago Area

Step5:- Compare the features for each clusters with image database to label that cluster. By applying the above step for each cluster in Otago image, we can obtain the following results.

- Two clusters labeled as football stadium .
- Fifteen clusters labeled as urban area.
- Seven clusters labeled as roads.
- Four clusters labeled as forest .

Step6:- Train back propagation neural network on the feature vectors for each cluster to determine the correct class for each feature vector. Before this, we need to determine some of parameters relate to BPNN .

Parameters:

maximum Number of epochs=20000.

Learning rate=0.8.

Momentum rate=0.0005

Maximum value of acceptable error =0.07

Result: The network enables from classification of all image objects with MSR=6.99905703928764E-02, after(3785) epoch. See Figure(4-12).

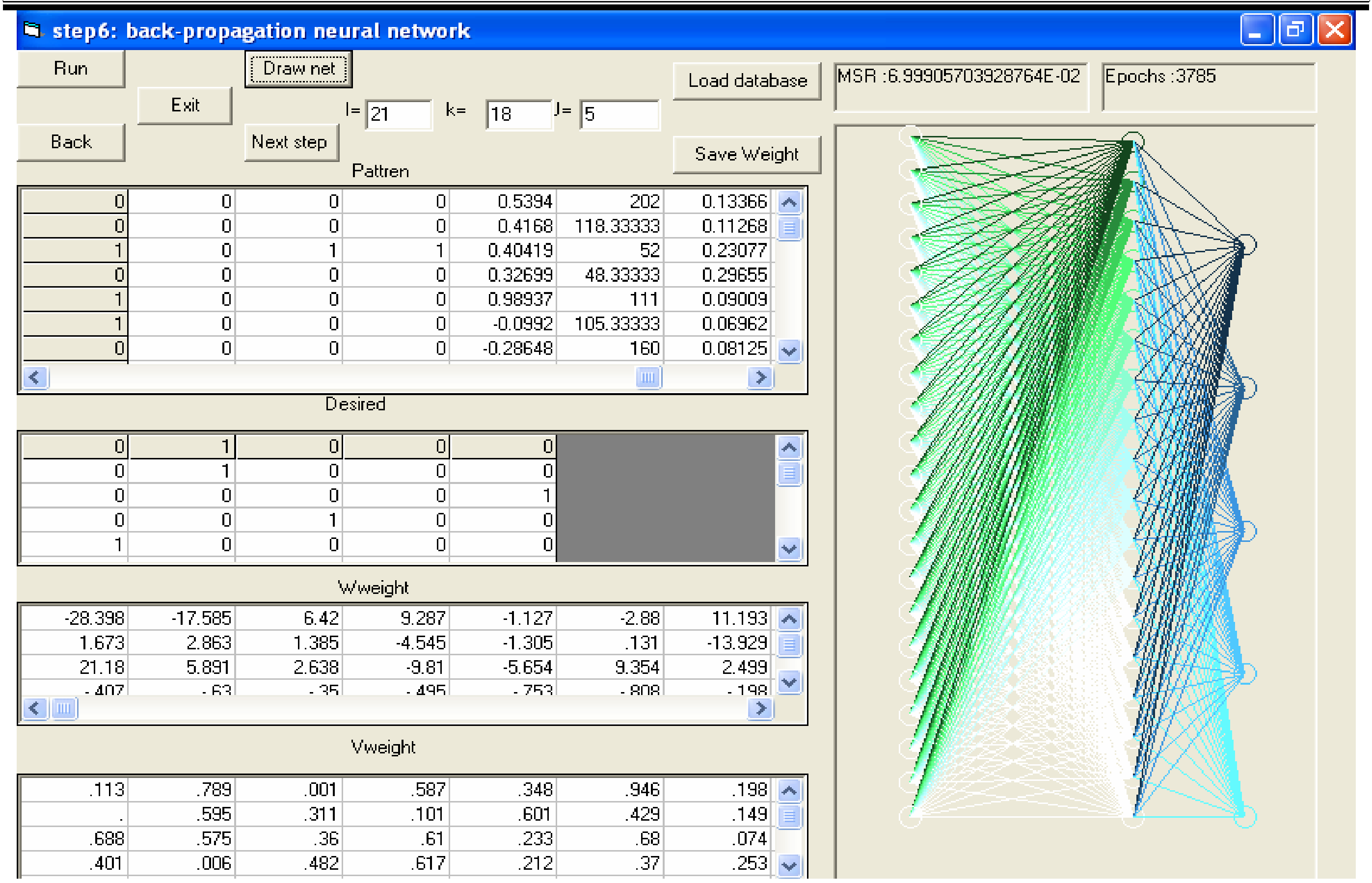


Figure (4-12) : Result of Back Propagation Neural Network for Case Study Two

Step7:- Use IF-Then Rule to form several rules that govern each class attributes . This step makes the system more precise, as follows:-

IF (hue=[-0.0992, 0.98937])and(saturation=[0.06962, 1])and (intensity=[50.33333, 230])and(pattern_uniform=1)and(pattern_near_uniform=0) and(pattern_non_uniform=1) and(shape_known=1)or(shape_unknown=1) and(texture_smooth=0)and(texture_rough=1)and(shadow_yes=1) and(shadow_no=0)and(associative_school=1) or(associative_road=1) or(associative_playground=1) and(associative_car=0) and(associative_water=0) and(associative_vegetation=0) and(associative_bridges=0) and(associative_scrolls=0) and(associative_car_attitude=0) Then class Urban area.

IF (hue= [-0.28648, 0.5403])and(saturation=[0.08125,1])and (intensity=[37.33333,202])and(pattern_uniform=0)and(pattern_near_uniform=0)and (pattern_non_uniform=1) and (shape_known=0)and(shape_unknown=1) and(texture_smooth=0) and (texture_rough=1)and(shadow_yes=0) and (shadow_no=1)and (associative_school=0) and(associative_road=0) and(associative_playground=0) and (associative_car=1) and(associative_water=0) and(associative_vegetation=0) and(associative_bridges=0) and(associative_scrolls=0) and(associative_car_attitude=0)]Then class Road.

IF (hue=[-0.58053,0.53982])and(saturation=[0.18681, 0.3271])and (intensity=[35.66667,91])and(pattern_uniform=0)and(pattern_near_uniform=0) and(pattern_non_uniform=1)and(shape_known=0)and(shape_unknown=1) (texture_smooth=0)and (texture_rough=1)and(shadow_yes=1) and(shadow_no=0)and (associative_school=0) and(associative_road=0) and (associative_playground=0) and(associative_car=0) and(associative_water=1) or(associative_vegetation=1) and(associative_bridges=0) and (associative_scrolls=0) and(associative_car_attitude=0) Then class Forest.

IF (hue=[0.40419, 0.51468])and(saturation=[0.02714, 0.23077])and (intensity=[52, 245.66667])and(pattern_uniform=1)and (pattern_near_uniform=0)and(pattern_non_uniform=0)and (shape_known=1)and(shape_unknown=0)and(texture_smooth=0)and (texture_rough=1)and(shadow_yes=1)and(shadow_no=0)and (associative_school=0) and(associative_road=0) and(associative_playground=0) and(associative_car=0) and(associative_water=0) and (associative_vegetation=0) and(associative_bridges=0) and(associative_scrolls=1) or(associative_car_attitude=1) Then class Football stadium

4-4 Case Study 3: Test Image for Bebedouro Area

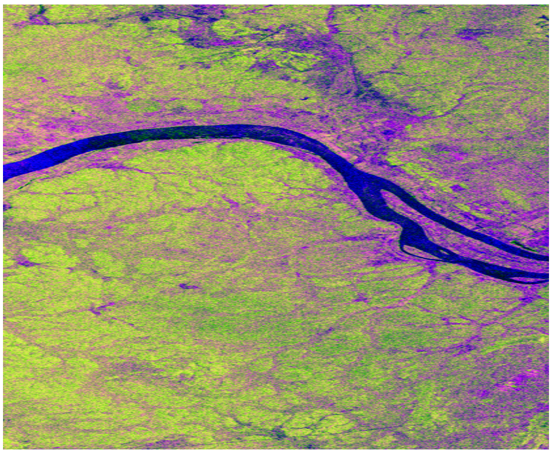


Figure (4-13) : Image for Bebedouro

4-4-1 A Sample of Image Data for the Experiment

This is an image showing seasonal changes at the hydrological test site of Bebedouro in Brazil. The image is centered at 9 degrees south latitude and 40.2 degrees west longitude. This image was acquired by the Space borne Imaging Radar-C ,image channels have the following color assignments: red represents data acquired on April 10; green represents data acquired on October 1; blue corresponds to the ratio of the two data sets. Agriculture plays an important economic and social role in Brazil. One of the major problems related to Brazilian agriculture is estimating the size of planting areas and their productivity. Due to cloud cover and the rainy season, which occurs from November through April, optical and infrared Earth observations are seldom used to survey the region. An additional goal of monitoring this region is to watch the floodplains of rivers like Rio Sao Francisco in order to determine suitable locations for additional agricultural fields. This area belongs to the semi-arid northeastern region of Brazil, where estimates have suggested that about 10 times more land could be used for agriculture, including some locations which could be used for irrigation projects. Monitoring of soil moisture during the important Summer crop season is of high priority for the future development and productivity of this region. In April the area was covered with vegetation because of the moisture of the soil and only small differences could be seen in (red, green, blue)band data. In October the run-off channels of this hilly region stand out quite clearly because the greenish areas indicated much less soil moisture and water content in plants. Total number of pixels in image (5184)pixel .

4-4-2 Result of Test:-

Step1:- Find the maximum number of clusters existing in that mage by drawing histogram of image and calculate the highest peaks in histogram(i.e., every pixel is considered a peak if it has 0.007 iteration from total number of pixels). Then split colors and fined histogram for each band. See Figure(4-14).

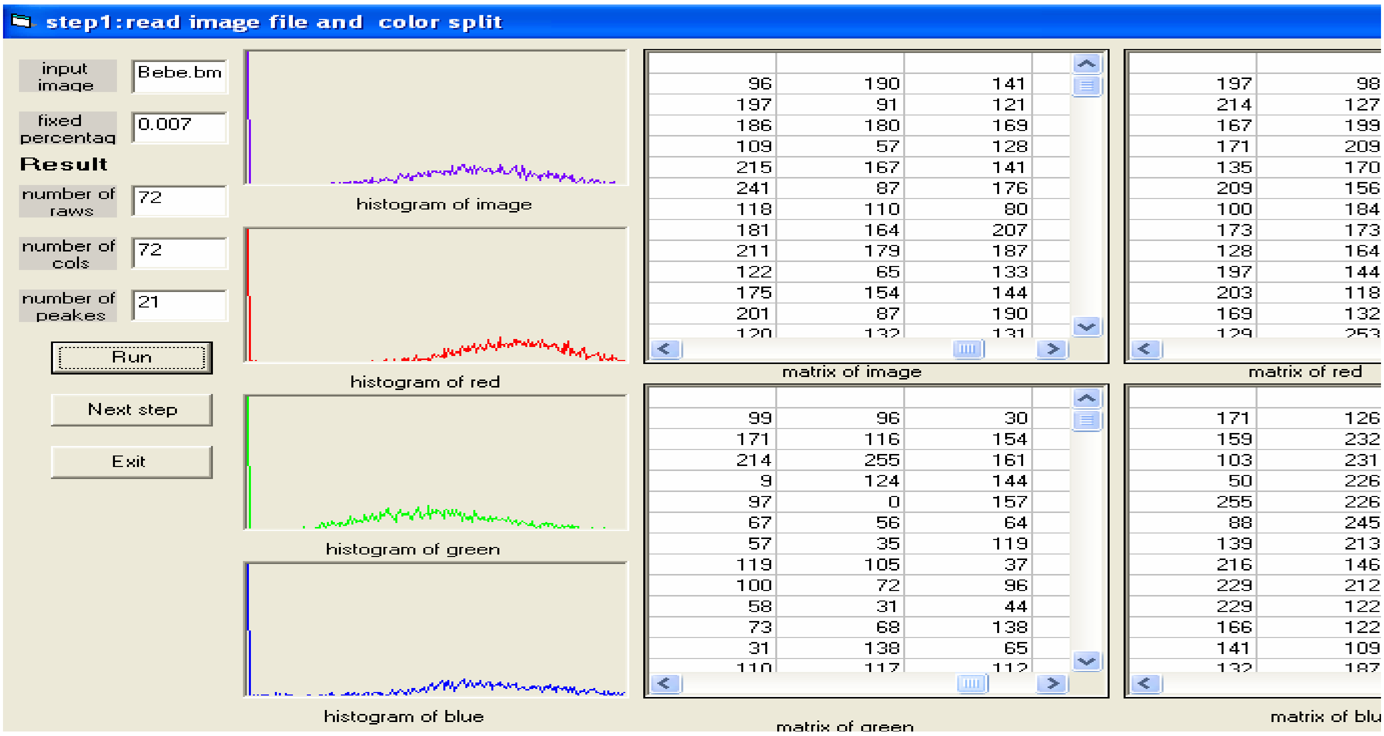


Figure (4-14) : Read the Image File and Color Split to Image for Bebedouro Area

Step2 :- Build database that describes each object in image for more detail see appendix and the visual features of this objects are encoded by using binary number(0,1). See Figure(4-15).

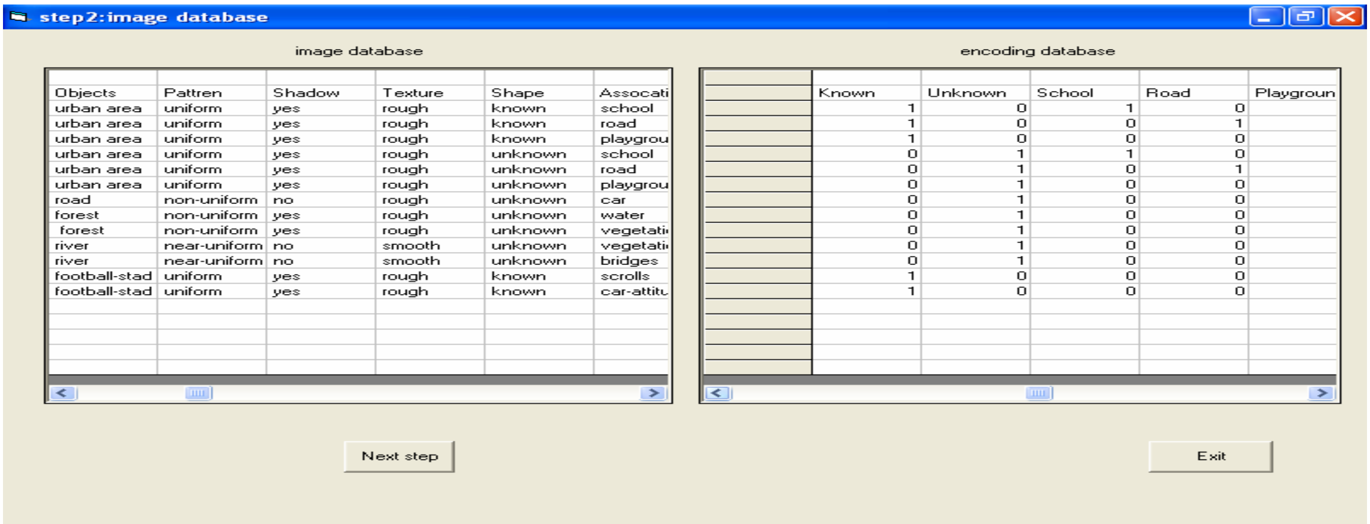


Figure (4-15) : Image database for Bebedouro Area

Step3 :- Apply breeder genetic clustering algorithm to find the actual number of clusters existing in that image data set (i.e. find best seed for each cluster and number of pixels found in that cluster). See Figure (4-16).

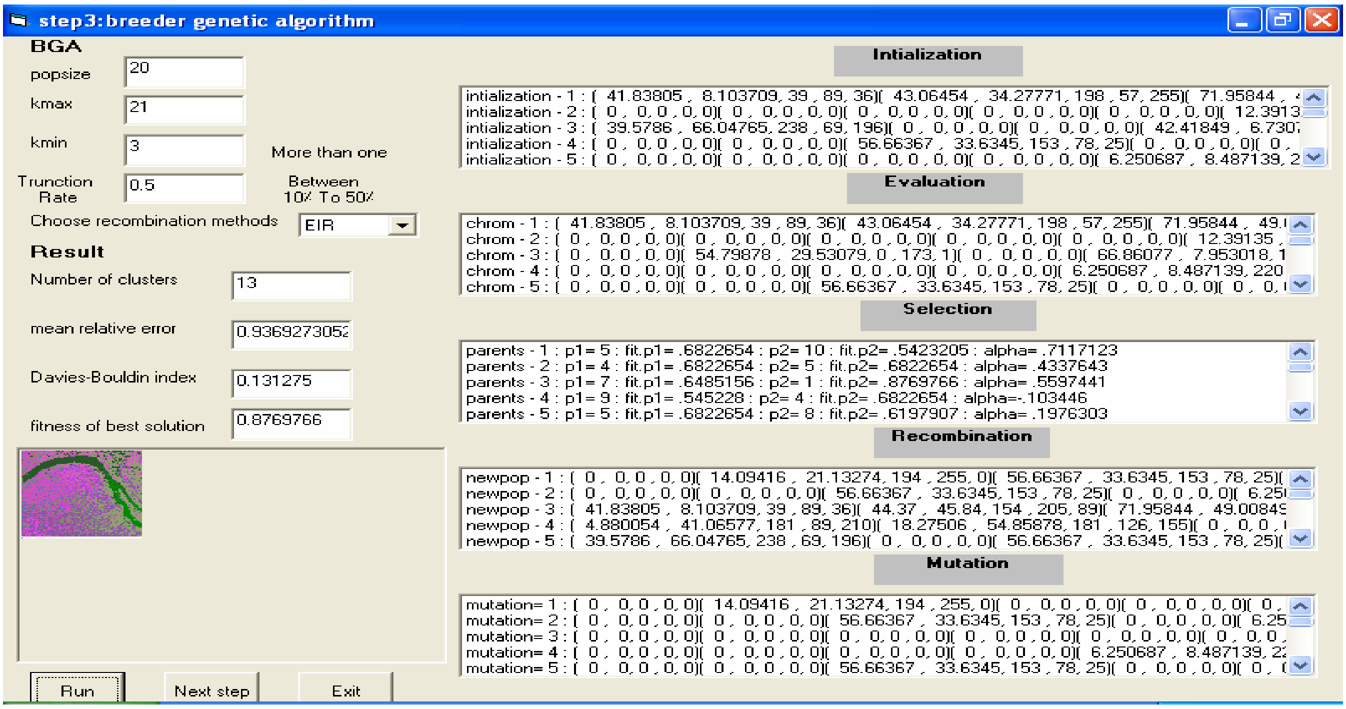


Figure (4-16) : Result of Breeder Genetic Algorithm by using Extended Intermediate Recombination

Table (4-3): Actual and computed values for the data sets of case study three

Cluster NO.	Center coordinates		Number Of pixels
	Actual	Compute	
1	(41.8,8.1,39,89,36)	(41.8,8.1,39,89,36)	447
2	(43.0,34.2,198,57,255)	(43.0,34.2,198,57,255)	238
3	(71.9,49.0,0,138,0)	(71.9,49.0,0,138,0)	231
6	(20.8,59.9,162,74,159)	(20.8,59.9,162,74,159)	342
7	(45.2,46.9,135,94,159)	(45.2,46.9,135,94,159)	593
8	(38.2,55.4,126,140,110)	(38.2,55.4,126,140,110)	502
12	(42.1,21.5,215,93,190)	(42.1,21.5,215,93,190)	509
16	(58.8,51.3,148,157,116)	(58.8,51.3,148,157,116)	953
17	(27.5,69.2,135,83,181)	(27.5,69.2,135,83,181)	148
18	(42.8,71.0,255,255,255)	(42.8,71.0,255,255,255)	143
19	(4.9,68.4,223,73,228)	(4.9,68.4,223,73,228)	111
20	(17.1,50.3,90,120,172)	(17.1,50.3,90,120,172)	223
21	(18.3,38.9,203,83,187)	(18.3,38.9,203,83,187)	744

Total number of pixels=5184

Total number of clusters=21

Number of actual cluster=13

Step4 :- Draw each cluster and calculate features for each one. Example of this we now explain the features of cluster number one. See Figure(4-17).

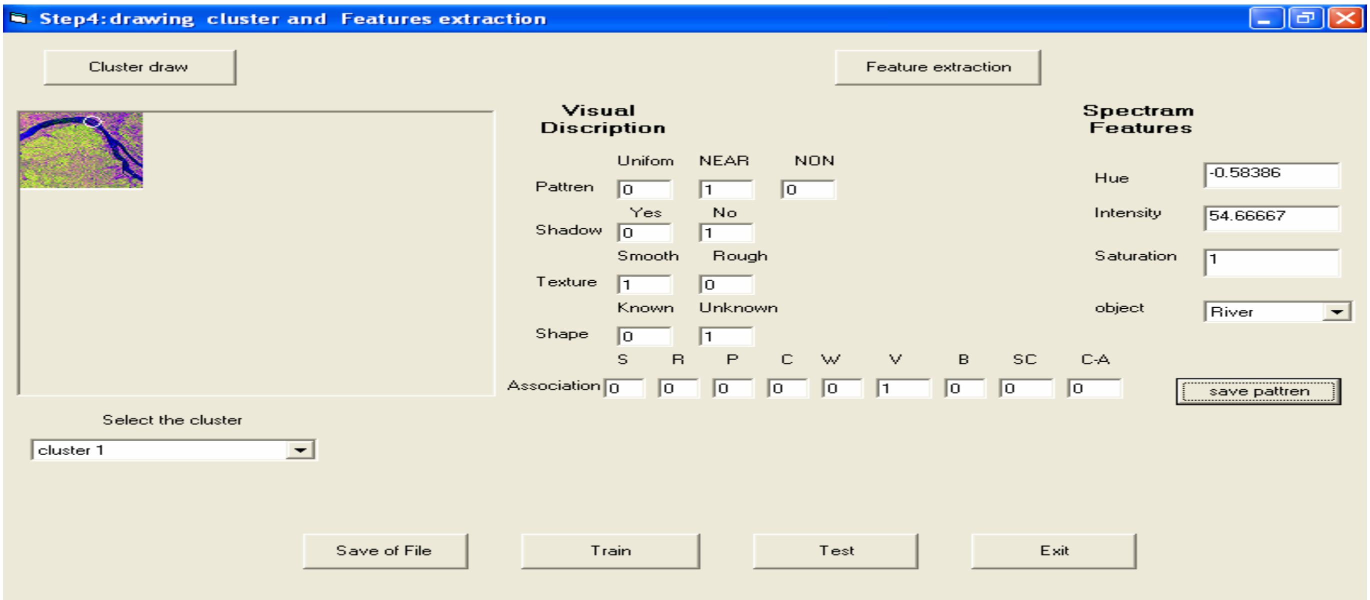


Figure (4-17) : Features of Cluster Number One of Bebedouro Area

Step5:- Compare the features for each cluster with image database to label that cluster. By applying the above step for each cluster in Bebedouro image, we can obtain on the following results.

- Three clusters labeled as water .
- Ten clusters labeled as forest.

Step6:- Train back propagation neural network on the feature vectors for each cluster to determine the correct class for each feature vector. Before this, we need to determine some of parameters relate to BPNN .

Parameters:

Maximum number of epochs=10000

Learning rate=0.55

Momentum rate=0. 09

Maximum value of acceptable error =0. 01

Result: The network enables from classification of all image objects with

MSR=9.99910859646935E-03, after(9282) epoch. See Figure(4-18).

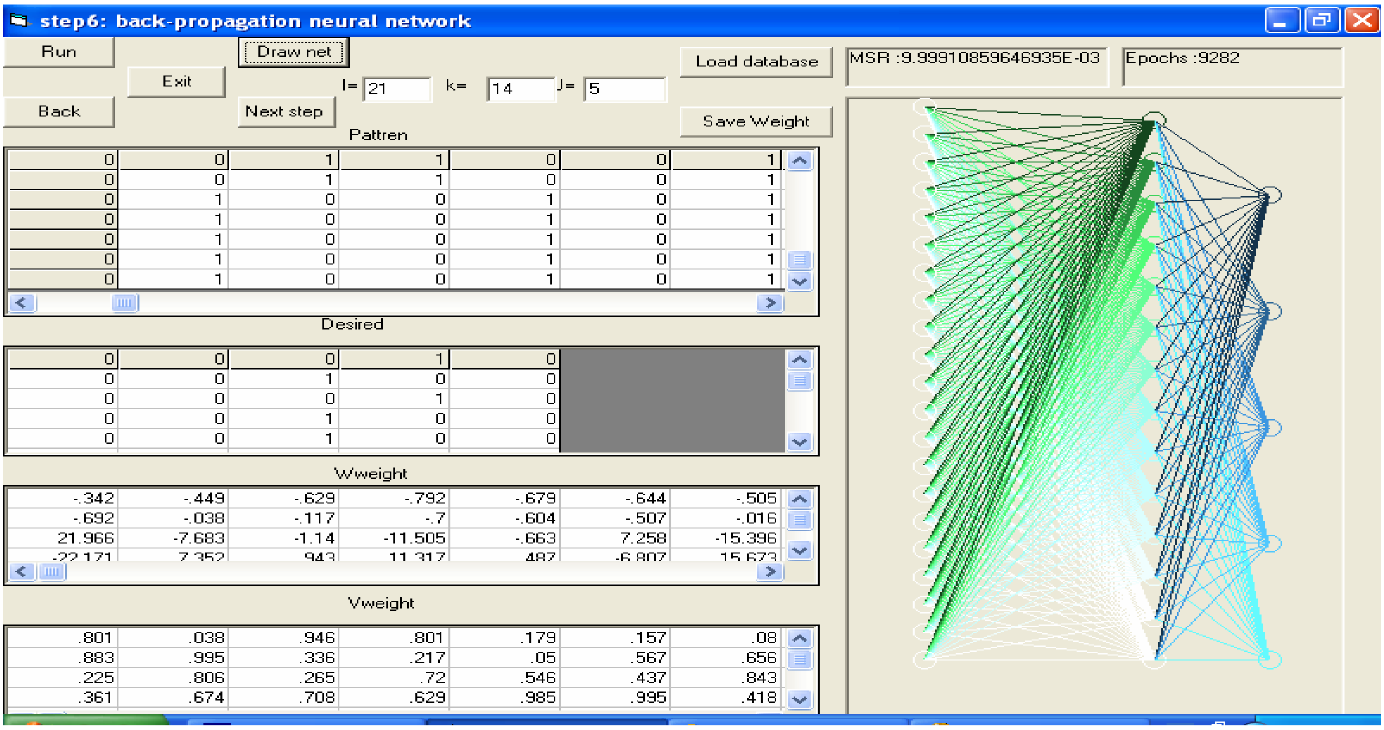


Figure (4-18) : Result of Back Propagation Neural Network for Case Study Three

Step7:- Use IF-Then Rule to form several rules that govern each class attributes . This step makes the system more precise, as follows:-

IF (hue=[-0.99944, 0.91534])and(saturation=[0.27320,1])and(intensity= [125.3333,255]) and(pattern_uniform=0)and(pattern_near_uniform=0) and(pattern_non_uniform=1)and(shape_known=0)and(shape_unknown=1) and(texture_smooth=0)and(texture_rough=1)and(shadow_yes=1) and(shadow_no=0) and(associative_school=0) and(associative_road=0) and(associative_playground=0) and(associative_car=0) and(associative_water=1) or(associative_vegetation=1) and(associative_bridges=0) and(associative_scrolls=0) and(associative_car_attitude =0)]Then class Forest.

IF(hue=[-0.99461,-0.41615])and(saturation=[0.43975,1])and (intensity=[46, 140.3333])and(pattern_uniform=0)and(pattern_near_uniform=1) and(pattern_non_uniform=0)and(shape_known=0)and(shape_unknown=1) and(texture_smooth=1)and(texture_rough=0)and(shadow_yes=0)and (shadow_no=1)and(associative_school=0) and(associative_road=0) and (associative _playground =0) and(associative_car=0) and(associative_water=0) and(associative _vegetation=1)and(associative_bridges=0) and(associative_scrolls=0) and(associative _car_attitude=0)]Then class River.

Chapter Five

Conclusions & Suggestions for Future Work

5-1 Conclusions

On the bases of the findings arrived at in the previous chapter, we can conclude the following :-

1. The advantage of applying soft classifiers is that the small classes will not vanish with the use of maximum likelihood.

2. To receive an acceptable classification result, the training areas need to be spectrally separable. This can be done with clustering or expert knowledge, and DSCOAPSI verifies this by applying breeder genetic clustering.

3. The bitmap format is suitable for the system since it deals with the image as multiple objects image in which each object is represented by a certain color.

4. The randomly estimation of the number of the clusters that are found in the image may lead to error in classification process. Therefore, DSCOAPSI can solve this problem by determining it automatically.

5. Forming several rules that govern each class attributes by using the IF-Then Rule format makes the system more precise because the features extracted from each class which are used to train NN are congruent to the conditions of this rule, while the resultant classes from NN are congruent to the actions of this rule. In other words the extracted rules are used to justify the inferred decisions.

6. DSCOAPSI confirms the ability to perform correct classification process of the objects of the images that are used in the testing process, despite of the different parameters for each image and the different objects found in that image.

5-2 Suggestions for Future Work

1. We suggest using another type of cluster validity measures and other type of distance measures.

2. We suggest using another type of features by dividing the image into uniform size blocks by using Discrete Cosine Transform(DCT)and then finding other types of features such as features depending on co-occurrence matrix or Gabor filter bank.

3. We suggest develop the system to work on additional bands from spectrum bands and also it use to classify other types of objects through extended image database.

4. We suggest use another type of neural network such as Bayesian Network or Self-Organization Feature Map.

REFERENCES

REFERENCES

[1] Timo.H, "Implementation And Algorithms Of A Tree Shape Parallel Computer Ph.D. Thesis, Tampere University of Technology, 1996.

[2] Sushmita.M and Yoichi.H, "Neuro-Fuzzy Rule Generation:Survery in Soft Computing Framework", IEEE Trnasaction on Neural Network,Vol. 11,No. 3, 2000.
Site: http://viz.csie.cgu.edu.tw/courses/soft/downloads/Readings/14.pdf

[3] Andrew.K"Soft Computing Industrial Application",Intelligent Systems Laboratory Lowa University, 2003.
Site: http: //www.icaen.uiowa.edu\~ankusiak

[4] Angela.B, "Soft Computing", England, 2003.
Site:http://www.tessella.com

[5] Ocordon.O and Herrera-Viedma. E,"Special issue on Soft Computing Applications to Intelligent Information Retrieval on the Internet",International Journal of Approximate Reasoning 34,PP. 89-95 ,2003.
Site:http://www.elsevier.com\locate\ijar

[6] Niblack.W, "An Introduction to Digital Image Processing "Prentice Hall International, 1986.

[7] Iman.A, "Determination of Industrial Water Behavior By Thermal Technique of Remote Sensing",M.Sc .Thesis,AL-Technology University ,2002.

[8] Lluis.B, "A Study in Function Optimization With The Breeder GeneticAlgorithm", 1999
Site:http://citeseer.ist.pus\cache\paper\cs

[9] Laurene.F,"Fundamentals of Neural Network Architectures,Algorithms,and Application", Prentic-Hall, 1994.

[10] Falco.I, Cioppa.A, Balio.R and Tarantino.E, "Investigating A Parallel Breeder Genetic Algorithm on The Inverse Aerodynamic Design", Naples-Italy, 2000.
Site:http://citeseer.ist.psu.edu/cache/papers/cs/1832/http:zSzzSzwww.irsip.na.cnr.itzSz~hotg SzpaperszSzppsn.pdf/defalco96investigating.pdf

[11] Peddle.R,"Empirical Comparison of Evidential Reasoning ,Linear Discriminate Analysis ,and Maximum Likelihood Algorithms For Alpine Load Cover Classification", Canadian Journal of Remote Sensing ,Vol. 19, No. 1, PP.31-44,1993.

[12] Peterson.M ,"Land Cover Classification-Boca Raton, Florida", geography environment, Florida Atlantic University ,1997.

[13] Schaale.M,"Land Cover Texture Information Extraction from Remote Sensing Image Data",Geosceience Department, Berlin University,2000.
Site:http://pcms.met.fuberlin.de/publications/asprs2000.pdf

[14] Nikola.K, Steven.A and Brendon.J, "The Application of Hybrid Evolving Connectionist Systems To Image Classification ", New Zealand, 2001.

[15] Sanghamitra.B and Ujjwal.M, "Genetic Clustering For Automatic Evolution OF Clusters and Application to Image Classification", the Journal of the Pattern Recognition Socirty, Vol.35, PP. 1197-1208,2002.
Site:http://www.elsevier.com\locate\patcog

[16] Leena.L and Jorma.A,"Rock Image Classification Using Non-Homogenous Textures and Spectral Imaging",Tampere University of Technology, Finland, 2003.

[17] Muhammad.F and Dzulkifli.L,"Comparison of Two Different Techniques for Complex Image Matching", Computer Science&Information Systems Department ,Malaysia University, Malaysia, 2002

[18] Andrew.M,"Fundamental of Remote Sensing", Canada, Canada Central for Remote Sensing ,2004.

[19] Scott.E, "Computer Vision and Image Processing :A Practical Approach Using CVIP Tools", Prentice-Hall ,New Jersey ,1998.

[20] Gonzalez .R and Woods. R," Digital Image Processing (2nd ed.)", New Jersey: Prentice Hall, 2002.

[21] Ahmed.K, "A Genetic Clustering For Image Segmentation",M.Sc. Thesis, Babylon University,2002.

[22] Morita.M, Sabourin.R , Bortolozzi.F and Suen.C, "Unsupervised Feature Selection Using Multi-Objective Genetic Algorithms for Handwritten Word Recognition", Canada, 2003.

[23] Nadia.B, "Cluster Validity Algorithms",Computer Science Department, Trinity College, 2004.
Site:http://www.cs.tcd.ie/Nadia.Bolshakova

[24] Kalyani.M and Sushmita.M,"Clustering and its Validation in a Symbolic Framework",Pattern Recognition Letters Journal , Vol. 24, PP. 2367-2376, 2003.
Site:http//www.elsevier.com\locate\patrec

[25] Beatriz.D, "Expermients in Image Segmentation for Automatic us Licens Plate Recognition", M.Sc.Thesis, Virginia University, 2004.

[26] Lluis.A,"A Case Study in Neural Network Training with Breeder Genetic Algorithm", Spain, 2001.
Site:http://citeseer.ist.psu.edu/cache/papers/cs/14387/http:zSzzSzwww.lsi.upc.eszSz~belanchezSzrecercazSzPIMA.pdf/a-case-study-in.pdf

[27] Falco.I, Iazzett.A, Natale.P and Tarantion.E, "Evolutionary Neural Networks for Nonlinear Dynamics Modeling", Italy, 1998.

[28] Heinz.M and Dirk.S,"The Science of Breeding and its Application to the Breeder Genetic Algorithm BGA", Journal of Evolutionary Computation ,Vol. 4, PP. 335-360, 1994.

[29] Quagliarella.D, Periaux.J, Poloni.C, Winter.G,"Genetic Algorithms and Evoluation Strategy in Engineering and Computer Science", John Wiley and Sons, New Yourk, October, 1998.

[30] Assad.S,"Hybrid Method(GA-BP)for Designing and Learning the Error Back Propagation Network With the Principle of Weight Decay", M.Sc. Thesis, Babylon University ,2000.

[31] Laith.M,"A Neural Network Based Artificial Vision System For Iraqi License Plate Recognition", Ph.D. Thesis ,AL-Technology University ,2003.

[32] Falco.I, Iazzett.A, Natale.P and Tarantion.E, "Optimizing Neural Networks for Time Series Prediction ", Advances in Soft Computing –Engineering Design and Manufacturing, Italy, 2000.

[33] Bart.K,"Neural Networks and Fuzzy Systems: Dynamical Systems Approach to Machine Intelligence", Prentice-Hall, 1998.

[34]Jacek.M,"Introduction to Artificial Neural System", JAICO Publishing House,Bombay,1997.

[35] Salah.M,"Hybrid System By Using Wavelet Transform in Neural Networks for Image Classification ", M.Sc.Thesis, Babylon University, 2003.

[36] Xin.Y,"Evolving Artificial Neural Networks", Proceedings of the IEEE,Vol. 87, No. 9, PP. 1423-1447, September 1999.

[37] Mark.S, "A Feed Forward Neural Network for Determining a User's Locations", 2000.
Site:http://www.cs.sfu.ca

[38] Valluru.B and Hayagriva.V,"C++ Neural Network and Fuzzy Logic",MIS Press, New York, 1993.

[39] Bill.W,"Neural Networks and Error Back-Propagation Learning",2003.
Site:http:// www.cs.unew.edu.au\~billw\mldict.html

[40] Nizar.G,Michel.Cand Nazha.B,"Unsupervised and Semi-Supervised Clustering :a Brief Survey", France, October 2004.

[41] Davies.D and Bouldin.D ,"A Cluster Separation Measure", IEEE Trnasaction on Pattren Analysis and Machin Intelligence. Vol. 1, PP. 224-227. 1979.

[42] Dermiriz.A , Bennett.K and Embrechts.M,"Algorithm Approach for Semi-Supervised Clustering",January 2002.
Site:http:// www.math.rpi.edu\~bennek

[43] Paolo.C,"Image Databases",2004.
Site:http://www.db.deis.unibo.it\courses\SI-LS\

[44] Ferat.S,"A Radial Basis Function Approach to a Color Image Classification Problem in Real Time Industrial Application",M.Sc.Thesis. Virginia University,1997.

[45] Zhiling.L,"The Design and Implementation of an Image Segmentation System for Forest Image Analysis", M.Sc.Thesis, Mississippi State University, 2001.

[46] Ebrahim.E, Haque.R and Esmel.E, "Extraction Rules From Trained Neural Network Using GA for Managing E-business", Applied Soft Computing Vol. 4, PP. 65-77, 2004.
Site:http://www.elserier.com\locate\asoc

[47]Swati.C, Sushmita.M and Sankar.K,"Neurofuzzy Classification and Rule generation of Modes of Radiowave Propagation",IEEE Transactions on antennas and Propagation,Vol. 51, No.4, April 2003.

[48] Sanka.K ,Sushmita.M and Pabitra.M,"Rough-FuzzyMLP:Modular Evolution ule Generation, and Evaluation", IEEE Transaction on Knowledge and Data Engineering ,Vol. 15, No. 1, January\Fubruary 2003.

APPENDIX

APPENDIX

DSCOAPSI

There are five data sets, representing five different output classes(objects). Each object describes by using visual and spectrum features as follow:-

*********************** Class1:Urban Area*************************

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.52989 110.66667 0.10542

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.34688 105.66667 0.00347

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 -0.89428 89.66667 0.00185

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.53988 127.33333 1

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.29367 144.33333 0.00508

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.54030 109.33333 1

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.54728 91.66667 1

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.52477 109 0.01834

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.52719 124.66667 0.00855

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.34688 97.33333 0.00342

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.00217 172.66667 0.05598

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0.54030 125 1

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.52989 110.66667 0.10542

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.34688 105.66667 0.00347

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 -0.89428 89.66667 0.00185

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.53988 127.33333 1

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.29367 144.33333 0.00508

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.54030 109.33333 1

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.54728 91.66667 1

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.52477 109 0.01834

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.52719 124.66667 0.00855

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.34688 97.33333 0.00342

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.00217 172.66667 0.05598

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0.54030 125 1

1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0 1 0 0 1 1 0 0 1 0 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0	0.50052	135	0.24444

1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0.5305 93.33333 0.48571

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.98937 111 0.09009

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 -0.0992 105.33333 0.06962

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.43208 230 0.07391

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.47068 126.33333 0.29551

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.52203 105 0.30476

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.5403 170 1

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.12822 105.33333 0.15506

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.52161 50.333333 0.18543

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.12822 146 0.14384

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.05054 163.33333 0.14449

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.48278 196 0.22959

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.31968 197 0.20305

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.07649 133 0.14286

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.50052 135 0.24444

1 0 0 1 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0.5305 93.33333 0.48571

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.98937 111 0.09009

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 -0.0992 105.33333 0.06962

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.43208 230 0.07391

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.47068 126.33333 0.29551

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.52203 105 0.30476

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.5403 170 1

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.12822 105.33333 0.15506

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.52161 50.333333 0.18543

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.12822 146 0.14384

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.05054 163.33333 0.14449

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.48278 196 0.22959

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.31968 197 0.20305

1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0.07649 133 0.14286

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1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0 1 0 0 1 0 1 1 0 0 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.31968	197	0.20305

1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0 1 0 0 1 0 1 0 0 1 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0 1 0 0 1 1 0 1 0 1 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.48278	196	0.22959

1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0 1 0 0 1 0 1 1 0 1 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.05054	163.33333	0.14449

1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0 1 0 0 1 1 0 0 1 1 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0	0.5403	170	1
1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0 1 0 0 1 0 1 0 1 1 0 0 0 0 0 0	0.12822	146	0.14384

APPENDIX

1 0 0	1 0	0 1	0 1	0 1 1 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0	1 0	0 1	0 1	0 1 1 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0	1 0	0 1	0 1	0 1 1 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0	1 0	0 1	0 1	0 1 1 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0	1 0	0 1	0 1	0 1 1 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0	1 0	0 1	0 1	0 1 1 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.5403	170	1
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.52161	50.333333	0.18543
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.12822	146	0.14384
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.05054	163.33333	0.14449
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.48278	196	0.22959
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.31968	197	0.20305
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.07649	133	0.14286
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.50052	135	0.24444
1 0 0	1 0	0 1	1 0	1 1 1 0 0 0 0 0 0	0.5305	93.33333	0.48571
1 0 0	1 0	0 1	0 1	1 1 1 0 0 0 0 0 0	0.98937	111	0.09009
1 0 0	1 0	0 1	0 1	1 1 1 0 0 0 0 0 0	-0.0992	105.33333	0.06962
1 0 0	1 0	0 1	0 1	1 1 1 0 0 0 0 0 0	0.43208	230	0.07391
1 0 0	1 0	0 1	0 1	1 1 1 0 0 0 0 0 0	0.47068	126.33333	0.29551
1 0 0	1 0	0 1	0 1	1 1 1 0 0 0 0 0 0	0.52203	105	0.30476
1 0 0	1 0	0 1	0 1	1 1 1 0 0 0 0 0 0	0.5403	170	1
1 0 0	1 0	0 1	0 1	1 1 1 0 0 0 0 0 0	0.12822	105.33333	0.15506
1 0 0	1 0	0 1	0 1	1 1 1 0 0 0 0 0 0	0.52161	50.333333	0.18543

1 0 0 1 0 0 1 0 1 1 1 1 0 0 0 0 0 0 0.12822 146 0.14384

1 0 0 1 0 0 1 0 1 1 1 1 0 0 0 0 0 0 0.05054 163.33333 0.14449

1 0 0 1 0 0 1 0 1 1 1 1 0 0 0 0 0 0 0.48278 196 0.22959

1 0 0 1 0 0 1 0 1 1 1 1 0 0 0 0 0 0 0.31968 197 0.20305

1 0 0 1 0 0 1 0 1 1 1 1 0 0 0 0 0 0 0.07649 133 0.14286

1 0 0 1 0 0 1 0 1 1 1 1 0 0 0 0 0 0 0.50052 135 0.24444

1 0 0 1 0 0 1 0 1 1 1 1 0 0 0 0 0 0 0.5305 93.33333 0.48571

***********************Class2:Road***********************

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.46272 84.66667 0.00551

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.53981 130 0.13846

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.53714 129.33333 0.10309

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.53991 78 1

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.52989 108.66667 0.00429

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.5394 202 0.13366

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.4168 118.33333 0.11268

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.28648 160 0.08125

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.5403 37.33333 1

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.182 124 0.22581

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.53919 157 0.3121

0 0 1 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0.35116 98.33333 0.14576

***********************Class3:Forest**********************

0 0 1 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 -0.48732 170 0.66471

0 0 1 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 -0.32514 131.66667 0.43797

0 0 1 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0.91534 129.33333 0.2732

0 0 1 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0.64692 125.33333 1

0 0 1 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0.05213 166 0.43976

0 0 1 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 -0.99944 133 0.37594

0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	0	255	1
0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	0.50855	174.66667	0.58206
0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	0.28362	127.33333	0.29319
0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	0.0887	157.66667	0.47357
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	-0.48732	170	0.66471
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	-0.32514	131.66667	0.43797
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.91534	129.33333	0.2732
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.64692	125.33333	1
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.05213	166	0.43976
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	-0.99944	133	0.37594
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0	255	1
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.50855	174.66667	0.58206
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.28362	127.33333	0.29319
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.0887	157.66667	0.47357
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	-0.48732	170	0.66471
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	-0.32514	131.66667	0.43797
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.91534	129.33333	0.2732
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.64692	125.33333	1
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.05213	166	0.43976
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	-0.99944	133	0.37594
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0	255	1
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.50855	174.66667	0.58206
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.28362	127.33333	0.29319
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.0887	157.66667	0.47357
0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	0.51468	82.66667	0.002161
0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	0	255	1
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.51468	82.66667	0.002161
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0	255	1
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.51468	82.66667	0.002161

0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0	255	1
0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	0.32699	48.33333	0.29655
0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	-0.58053	35.66667	0.3271
0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	0.53982	91	0.18681
0 0 1	1 0	0 1	0 1	0 0 0 0 1 0 0 0 0	0.14868	48	0.22917
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.32699	48.33333	0.29655
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	-0.58053	35.66667	0.3271
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.53982	91	0.18681
0 0 1	1 0	0 1	0 1	0 0 0 0 0 1 0 0 0	0.14868	48	0.22917
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.32699	48.33333	0.29655
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	-0.58053	35.66667	0.3271
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.53982	91	0.18681
0 0 1	1 0	0 1	0 1	0 0 0 0 1 1 0 0 0	0.14868	48	0.22917

**********************Class4:River**********************

0 1 0	0 1	1 0	0 1	0 0 0 0 0 1 0 0 0	-0.41615	46	1
0 1 0	0 1	1 0	0 1	0 0 0 0 0 1 0 0 0	-0.99461	140.33333	1
0 1 0	0 1	1 0	0 1	0 0 0 0 0 1 0 0 0	-0.58386	54.66667	1
0 1 0	0 1	1 0	0 1	0 0 0 0 0 0 1 0 0	-0.41615	46	1
0 1 0	0 1	1 0	0 1	0 0 0 0 0 0 1 0 0	-0.99461	140.33333	1
0 1 0	0 1	1 0	0 1	0 0 0 0 0 0 1 0 0	-0.58386	54.66667	1
0 1 0	0 1	1 0	0 1	0 0 0 0 0 1 1 0 0	-0.41615	46	1
0 1 0	0 1	1 0	0 1	0 0 0 0 0 1 1 0 0	-0.99461	140.33333	1
0 1 0	0 1	1 0	0 1	0 0 0 0 0 1 1 0 0	-0.58386	54.66667	1
0 1 0	0 1	1 0	0 1	0 0 0 0 0 1 0 0 0	0.53781	89	0.67415
0 1 0	0 1	1 0	0 1	0 0 0 0 0 1 0 0 0	0.53981	101	0.00891
0 1 0	0 1	1 0	0 1	0 0 0 0 0 1 0 0 0	0.50550	143	0.13986

***********************Class5:Footbal-Stadium***************

1 0 0 1 0 0 1 1 0 0 0 0 0 0 0 0 1 0	0.40419	52	0.23077
1 0 0 1 0 0 1 1 0 0 0 0 0 0 0 0 1 0	0.51468	245.66667	0.02271
1 0 0 1 0 0 1 1 0 0 0 0 0 0 0 0 0 1	0.40419	52	0.23077
1 0 0 1 0 0 1 1 0 0 0 0 0 0 0 0 0 1	0.51468	245.66667	0.02271
1 0 0 1 0 0 1 1 0 0 0 0 0 0 0 0 1 1	0.40419	52	0.23077
1 0 0 1 0 0 1 1 0 0 0 0 0 0 0 0 1 1	0.51468	245.66667	0.02271

الخلاصة

يقدم هذا البحث طريقة لتصميم نظام برمجي يستخدام التقنيات الهجينة ممثلة بـ (**Soft Computing**) لتصنيف الكيانات من الصور الجوية وصور الأقمار الاصطناعية اعتمادا على خصائصها وبأقل خطأ ممكن.

حيث إن هذه الصور عادة تتألف من سبع حزم أما العمل ضمن هذا البحث فقد ركز على التعامل مع ثلاث حزم (**الحمراء ، الخضراء والزرقاء**) . هذا البحث اختص بتصنيف خمس أنواع من الكيانات (منطقة حضرية، منطقة غابات ، انهار، طرق، ملاعب كرة قدم).

طبقاً لذلك تم اولاً بناء قاعدة بيانات تصف تلك الكيانات بالاعتماد على خصائصها. ثم استخدامت خوارزمية تطورية من نوع خوارزمية التوليد الجيني **Breeder Genetic Algorithm** وذلك لإجراء عملية عنقدة جينية لتجزئة الصورة وتجهيزنا بعدد العناقيد الموجودة في الصورة. ولتجنب حدوث تداخل العناقيد مع بعضها فقد تم استخدام احد مقايس تحقق خوارزميات العنقدة وهو (**Davies-Bouldin index**)كدالة صلاحية لتلك الخوارزمية ، وناقشنا أربعة طرق للتزاوج فيها هي (التزاوج المتقطع، التزاوج الموسع الخطي، التزاوج الموسع الحالي، التزاوج المضبب).

ثم تم استخلاص نوعين من الخصائص لكل عنقود وهي خصائص مرئية وتضمنت (النمط**Pattern**, الشكل **Shape**، الظل **Shadow**، التركيب**Texture**، التطابق **Association**)، وخصائص إحصائية وتمثلت بالخصائص الطيفية التي اشتملت على (الشدة اللونية **Intensity**،اللون النقي **Hue**، الإشباع **Saturation**) .

بعدها تم توظيف شبكة عصبية ذات تغذية امامية من نوع شبكة انسياب الخطأ خلفاً **Error Back Propagation Neural Network** لتحديد الصنف الذي ينتمي إليه كل متجه واصفات .

وكمرحلة أخيرة استخدمنا الـ(**IF-Then Rule**) لصياغة بعض القوانين التي تحكم مواصفات كل صنف .