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Satellite Image Classification Using Image Encoding and Artificial Neural Network

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***Abstract*— *The conceptual variety in the satellite images cause some differences in color ingredients and fine details that usually need to be distinguished for purpose of classification. Image classification is carried out generally using a five to seven color bands that are reflect signitures of the objects found in the landcover. The geographic information system (GIS) uses such signitures to classify the different items appeared in the satellite image. The classification tools used in GIS became traditional due to they used for years, which do not provide satisfactory results. Therefore, the developments are required to keep abreast of advances in technology. This paper presents a method for satellite image classification aiming at handling the problem of satellite image classification. The newly proposed method is based on two phases: Image encoding and classification based Artificial Neural Network (ANN). The first phase depends on encode the satellite image. Whereas, the second phase depends on classifying the image using the ANN, in which the input materials are an achieved codes that resulted from the first phase, while the output are the classified image regions.The classification results gave 99% classification accuracy, which is a promising score in comparison with related litritures.*

***Keywords*— *Artificial Neural Network (ANN), Image encode, Supervised training, Remote Sensing.*

I. INTRODUCTION

Remote sensing is a field of studying data of land cover, such data may be given either by satellite imagery or LiDAR. Remotely sensed imagery can be used for many applications like land use monitoring, reconnaissance missions, and estimation of environmental damage, urban planning, radiation monitoring, growth regulation, soil evaluation, and crop production assessment. The classification of this imagery is essentially an indispensable part of these applications [1], Satellite image classification is the most important task includes computer-assisted techniques for data analysis, processing and classification. Many techniques are introduced for image classification, such as: neural network (NN), decision trees, genetic programming, statistical machine learning and other analysis methods [2]. Satellite image classification includes mainly two stages: segmentation and classification. The objective of image segmentation is to partition the image into parts are strongly correlated according to the conceptual contents of the image. Whereas, the classification aims to assign a specific label for each image segment in terms of predefined groups or classes of known attributes [3], Neural networks have emerged as an interesting tool for classification. Recent researches refer to the power of neural network based classification [1]. Neural networks provide flexibility and the ability to learn complex data, it is used to identify classes for classifying image data. Thus, one can get highly accurate and robust results by providing small test samples. Moreover, the neural network approach avoids the problem of specifying how much influence each source in statistical multi-source analysis. Therefore, the neural network approach becomes more preferable for multisource remote-sensing data classification [4].

II. REMOTE SENSING AND SATELLITE IMAGES

Remote sensing is the science of acquiring information about the Earth's surface without actually contact with it, The sensor is designed based on two techniques: passive sensor, or active sensor. Passive sensor receives the illumination reflected by objects from an additional light source, such as the sun. Optical sensors are usually passive sensors used to collect different spectral ranges (or, bands), which are differ in their number and width per sensor. Active sensors send radiation to the targets and receive the scattered reflectance. Radio detection and ranging (Radar) is active remote sensing, Light Detection and Ranging (LiDAR) is another active remote sensing [5], Satellite images are usually collected through multispectral technology, which captures information outside the normal human perceptual range; including infrared, ultraviolet, X-ray, acoustic or radar data. The information is usually represented in visual form by mapping the different spectral bands to RGB components. If more than three bands of information are used, then the dimensionality can be reduced [4]. Classification of remotely sensed images is one of the most challenging areas to deal with, because so many techniques, tests, and datasets are continually being updated, added to, or tried out. Furthermore, image segmentation is preprocessing stage is usually carried out before classification [2].

III. LITERATURE SURVEY

There are a number of papers focused on satellite image classification and neural network. Some approaches were developed for achieving more efficient techniques to serve a specific application, while others are denoted for serving the scientific documentation. In the following, the most significant literatures are mentioned in details:

- In 2005, Mayank Toshniwal, suggest feed-forward neural networks in the area of satellite image segmentation. New approaches and innovative increments have been added to the standard thoughts. Provides suitably developed neural network architecture with high accuracy. Obtained

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accuracy and efficiency in terms of standard parameters to achieve accurate image segmentation. It is concluded that there is an ability to improve the timeliness of the segmentation, and solving problems of insufficient training sets [4].

- In 2013, Gowri Ariputhiran, S. Gandhimathi, proposed about the classification and extraction of spatial features in urban areas of high resolution multispectral satellite image. Preprocessing is done for a multispectral satellite image using a Gaussian filter to remove the noise which is present in the image. Then the features are extracted from the filtered image using Gray Level Co-occurrence Matrix (GLCM). Finally, extracted features are classified using Back Propagation Artificial Neural Network (BPANN) and the performance is analyzed based on its accuracy, error rate and sensitivity, Finally the multispectral image is classified into multiple regions based on the training data. The classification results were up to 94.59%, which ensures that the classification has good accuracy in all types of multispectral satellite images [6].
- In 2014, S. Praveena, Dr. S. P. Singh, presented a hybrid clustering algorithm and feed-forward neural network classifier for land-cover mapping of shade, trees, building and road. It starts with the single preprocessing step to make the image suitable for segmentation. The pre-processed image is segmented by use the hybrid genetic-Artificial Bee Colony (ABC) algorithm that is developed by hybridizing the ABC and genetic algorithms to generate the effective segmentation in satellite image and classified by use feed-forward neural network classifier. The results showed high accurate classification [3].

IV. THE ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) is an information processing paradigm which is like the shape of the brain neuron and it is used in artificial intelligence [1]. The Artificial neuron consists of the following five items as shown in Figure 1 [7]:

- Neuron, which is the basic elements where information processing occurs.
- Connections, which are the links by which each neuron is connected to other neurons in a network, to allow to the signals passed through them.
- Weights, which are the information used by the network to solve a problem, each connection link has an associated weight.
- Activation function, which is usually a nonlinear function apply on the outputs.
- Inputs/Output signals.

The advantages of using artificial neural networks include the following four subjects: Adaptive learning, which is the ability to learn how to do tasks based on the data given for training or initial experience. Self-Organization, where the ANN can create its own organization or representation of the information it receives during learning time. Real Time Operation, where the ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability. And finally, the Fault Tolerance via Redundant Information Coding, where the partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with the major network damage [8]. The multilayer layer perceptron (MLP) is one of the most widely applied and researched ANN models. The MLP networks are normally applied to performing supervised learning tasks, which involve iterative training methods to adjust the connection weights within the network [9].

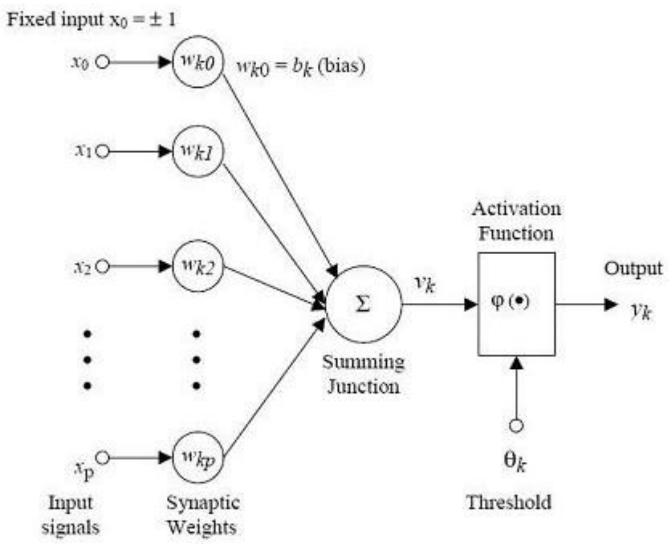

Fig. 1. Artificial neuron [8].

V. THE PROPOSED METHOD

The proposed satellite image classification consists of two phases: training, and classification. Each phase contains some stages within, Figure 2 shows the detailed stages of each phase, In the proposed method, the training phase is responsible on enroll the database information that needed to implement the next phases. The classification phase is designed to employ the information stored in the database for classification purpose. Both the training and classification phases are based on using back propagation artificial nueral network (BPANN) to recognize input features that resulting a classified image. This requires to pass through a preprocessing and preparing stages. The following sections give more explanations about each stage of the proposed method.

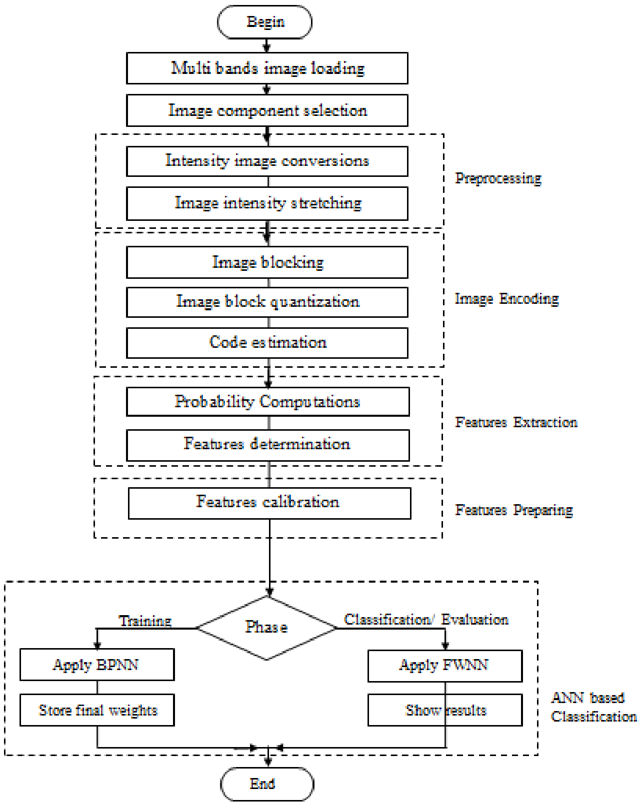

Fig. 2. Block diagram of the proposed satellite image classification.

A. *Image Preprocessing*

Image preprocessing is primary stages made to improve the visual appearance of the test image. These stages rely on the intensity of pixels without affecting the correlation of adjacent pixels. Such improvement leads to enhance the distinguishing between image cues, which can be achieved by adopting the following two steps:

- *Intensity Image Conversion*

Intensity image is a grey image in which the value of each pixel is a single sample representing only spectral intensity information. At present stage, the shades of grey scaled image have values in between 0 and 255. The grey scaled intensity image (I) by using Equation (1) is resulted by computing the intensity of light for each pixel in the three image components.

$$I = 0.299\times f_R + 0.587\times f_G + 0.114\times f_B \quad \ldots (1), [4]$$

f_R Refers to the red color in the image, f_G Refers to the green color in the image, f_B Refers to the blue color in the image.

- *Image Intensity Stretching*

Intensity stretching G in Equation (2) is an enhanced process impact the contrast of the image. It increases the contrast up to the full amount. The contrast is the difference between the maximum (I_{max}) and minimum (I_{min}) pixel intensities found in the image. The formula for stretching the histogram of the image to increase the contrast is given as follows:

$$G=(I- I_{min} \;/\; I_{max} - I_{min})* 2^{bpp} \quad \ldots (2), [10].$$

where the *bpp* is the bit per pixel (i.e. Bit rate). In the present case, Landsat provides an image of bit rate is 8 bpp, so levels of gray are 256.

TABLE I. Details of data used for training.

Classes	Number	Color	Name of Class	%
Class 1	30909	Blue	Water	3%
Class 2	354411	Red	Residential(non contain Vegetation	34%
Class 3	191079	Green	Vegetation	18%
Class 4	357446	Maroon	Residential(contain Vegetation	34%
Class 5	110639	Yellow	Open Land	11%
Total	1044484			

B. *Image Encoding*

Image encoding stage is used to change the representation of image regions with others are more appreciable. The encoding is a computer procedure based on partitioning the image into small parts, each possesses a specific details can be processed to estimate the corresponding code that describe that image region.

- *Image Blocking*: Therefore, the test image is partitioned into overlapped blocks; each block is describing the behavior of the pixel lies in the center of the block. Then, a code array is estimated for each block to reflect the specific content of the image in that region.
- *Block Quantization*: The image block quantization is carried out by the following procedure: for a given block Bij, one can assume that the number of grey levels is (C). for example; if the number of ranges is five, then C=1, 2, 3, 4, and 5. Such that NC is one dimensional array in which N1 is the number of pixels lies in the first grey range (R1), N2 is the number of pixels lies in the second grey range (R2), and so on till N5 of the last fifth range (R5). Then, a specific two dimensional quantized array Q(i,j) with same size of given block is created, the elements of this array is pointer refers to the range that the pixel of the original block lie on, i.e. the elements may be one of the values: 0, 1, 2, 3, and 4 in corresponding to the ranges R1, R2, R3, R4, and R5. Figure 3 shows an example of quantized block corresponding to the original one.

36	143	78
237	112	82
92	41	196

(a) Original block.

0	3	2
4	3	1
1	0	3

(b) Quantized block.

Fig. 3. Quantized block corresponding to original one.

C. *Code Estimation*

It is intended to produce a two dimensional code array to represent the intensity signature of each pixel in the test image. This code array is determined by computing the number of transitions between successive quantized grey levels in the same image block. Therefore, the computing transition is a two dimensional array T(m,n), where both m and n are equal to C. Each element in T(m,n) is the number of right horizontal transitions (at zero angle direction) between Pixel pointers in Q(i,j) that corresponds to the location m, n. Implies, T(0,0) is equal to the number of existing two horizontally adjacent pixels, each has a pointer value of 0, while T(0,1) is equal to the number of existing two

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horizontally adjacent pixels, in which the pointer value of the first pixel is 0 and the pointer value of the second is 1. As a result, the code array represents the frequency of appearing any two grey levels to be adjacent in the current block. Figure 4 shows the code array of the quantized image block.

0	1	0
2	1	0
1	0	2

(a) Quantized block.

	0	1	2
0	0	1	1
1	3	0	0
2	0	1	0

(b) Estimated code array.

	0	1	2
0	0	3	0
1	1	0	1
2	1	0	0

(c) Transpose code array.

	0	1	2
0	0	4	1
1	4	0	1
2	1	1	0

(d) Transpose +Estimated.

Fig. 4. Transpose and Estimated code array block and total of them result.

VI. Results and Discussions

The development of satellite imagery brings about an easy way to extract useful information on land cover. Consequently, the behavioral performance of satellite imagery data analysis is examined using validation and assurance techniques. In the present work, there are two considered paths; training and classification. The training is useful to indicate the basic information about image classes that represented by some specified statistical features, while the classification uses the same features to produce the final classification results in terms of training results. Results validation is carried out for assurance purpose. The validation includes a clear picture about the performance of the used algorithms mentioned in the previous chapter. Also, there is a detailed explanation related to the results achieved through implementing each stage in the proposed classification method. The results are presented in figures and tables including the final percentage of classification. Then, quantitative and qualitative analysis is estimated to evaluate the performance of the proposed classification method. Moreover, the implementation of the proposed method was designed by Visual Studio 2012 C# programming language that executed under Windows 8 operating system. The dedicated classification method was designed to include a package of preprocessing and post processing that mentioned previously, also it shows pretty interface for displaying the results of each stage individually. The following sections show more details about the results and discussions of the employed method.

A. Training DataSet

For the purpose of supervised training, a specific classified image is used as reference images. This reference image is used to determine the class that each pixel belongs to in the material image. Figure 5 shows the reference classified image for year 2000 used to train the designed BPANN, while Table I presents the information on image classes of the reference image. Such reference image was achieved from the Iraqi Geological Survey Corporation (IGSC), which contains five classes as shown in Figure 5.

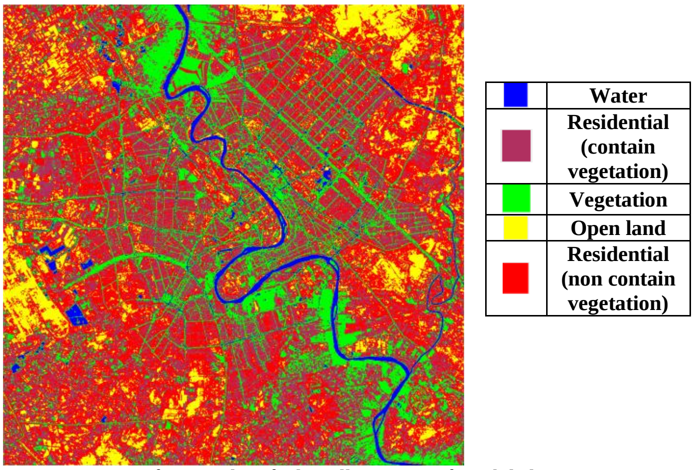

Fig. 5. Reference classified satellite image of Baghdad in 2000.

B. Training Phase Result

In the training implementation, the number of iterations through research and experimentation was determined to be 1000 for each training process of one pixel or till reaching a proper accuracy score (i.e. mean square error; MSE= 0.001), in which the used learning ratio is 0.5. These restriction values gave the most confident results, where the weights begins with random initial values between 0-1 that adapted time by time till reaching true values as Figure 6 shows, Figure 7 shows the weights behavior with more iteration. Whatever the initial value is, it is found that the weight is biased towards its true values with 1000 training iterations, they are far away from their true values at events when increasing training iterations, Also, it is noticeable that the weights settle at certain values at the last iterations, and there is no change may occur on them with increasing the training iterations, In such case, the MSE that computed between the result of BPANN and the true class value becomes smaller at each training iteration till reaching the best values of the weights. Figure 8 shows the behavior of MSE of training the weights for a sample pixel, it is shown that the MSE approaches the zero for enough specific training iterations, while Figure 9 shows the behavior of MSE for more training iterations, in which the MSE does not identifying the zero value, but it is still continuing at specific small amount. The behavior of the weights is almost directed toward true values during the training time, and it may gained little increasing at the decreasing mode due to spectral inhomogeneity found in current image block, which showed non monotonic behavior for weights corrections. In spite of that, the weights remain to embraces the corrected path toward the true values till terminating the training phase. This result ensures that the number of iteration and learning ratio was sufficient to obtain acceptable classification results.

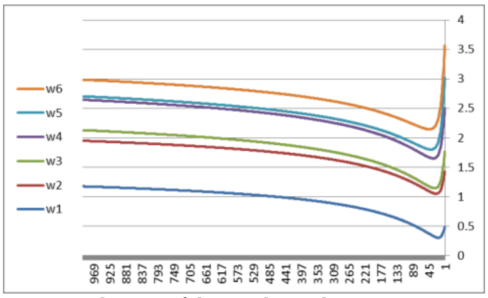

Fig. 6. Behaviors of the weights with 1000 iterations.

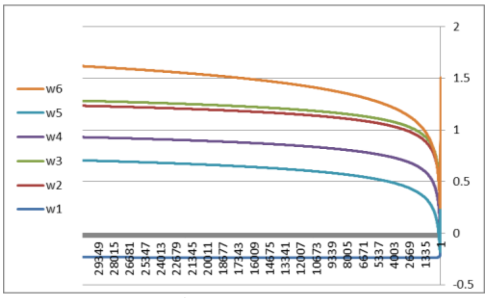

Fig. 7. Behaviors of the weights with more iterations.

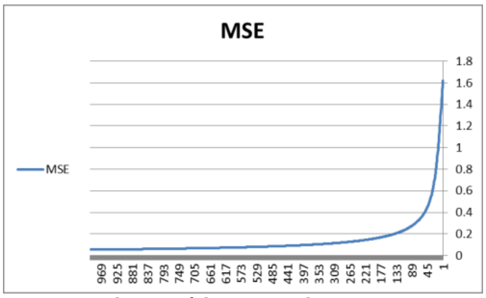

Fig. 8. Behavior of the MSE with 1000 iterations.

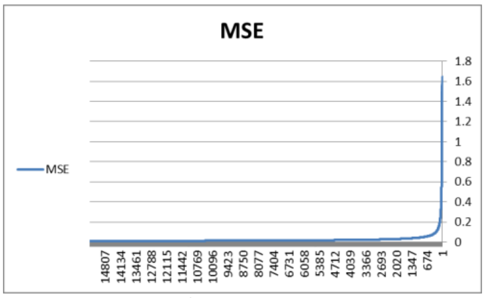

Fig. 9. Behavior of the MSE with more iterations.

C. Classification Phase Result

The classification process depends on using the training database that containing an appropriate final weights for resulting the classified image. Figure 10 displays the classification result of same reference satellite image using the proposed BPANN, while Table II shows some results statistics that needed to evaluate the classification performance; these statisticsare the number (Np) of pixels and classification percentage (Pc) for each class in the resulted classified image. The classification percentage in such case is a partial percent represents the partial area of each class according to the classification results, and the summation of all partial percents gives 99%. It is shown that the proposed BPANN could classify all the image pixels efficiently, where the final classification score was 99%, which indicates that there is no pixel in the given image is left without classification.

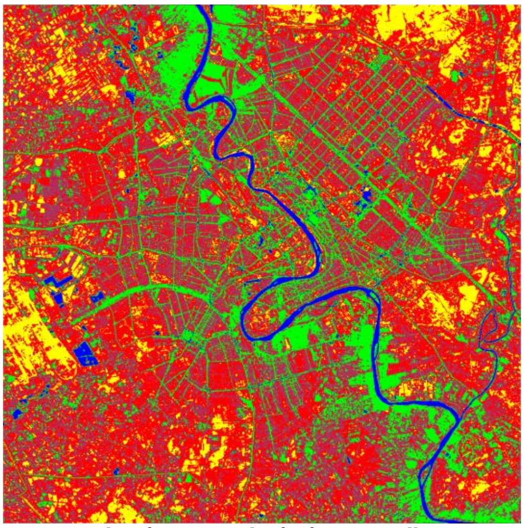
Fig. 10. Classification result of reference satellite image.

TABLE II. Classification results.

Classes	Color	Name of Class	N_p	P_c
Class 1	Blue	Water	30909	3%
Class 2	Red	Residential(non contain Vegetation	354411	34%
Class 3	Green	Vegetation	191079	18%
Class 4	Maroon	Residential(contain Vegetation	357446	34%
Class 5	Yellow	Open Land	99977	10%
Total	10433822			99%

D. Validation and Generalization Result

The validation and generalization test is the use the proposed method of BPANN for classifying another satellite images that not classified in previous time, mean use another data not used in training the neural network. To implement such process, the satellite image is used. Figures 11 shows the classification result of satellite images for the period 2003 Table III lists the accuracy measures of the classification results It is shown that the accuracy ratio value of true classification is 98% of this image compared to the original classification, Where a mis classification in the class one percent 1%, and class two in percent 1%, that mean the mis classification percent in all the resulted image is 2%. the designed system succeeded in correctly classifying the validation image by a percentage accurisy 98%, which means that the proposed system has achieved generalization and can successfully classify new images data in good percentage, Table III shows the results of evaluation, in which N_{P1} is the number of pixels in each class in resulted classified image, N_{P2} is the number of pixels in each class in real classified image, T_C is the number of true classified pixels in classified image comparing with the real classified image, P_{TC} is the classification percent of true classified pixels in classified image, F_C is the number of false classified pixels in classified image in comparison with the real classified image, and P_{FC} is the classification percent of false classified pixels in classified image, The true determination of classes dataset makes the classification results to be more confident. It was observed

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that the proper block size is greatly helping the classifier to determine the best class for each block in the test image, which absolutely leads to optimal classification. The maximum classification error occurs in the water class which is an extended homogeneous region, this error is absolutely come from the error happen in the partitioning stage, which can be exceeded when using non uniform partitioning method like quadtree. Whereas, a minimum classification error occurs in residential classes, which are more detailed classes, this indicates that the proposed method was successful in classifying the satellite images, and ensure better performance and high efficiency of the employed method.

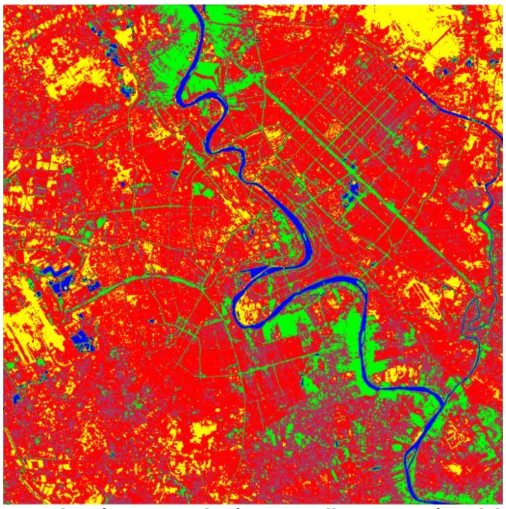
Fig. 11. Classification result of 2003 satellite image of Baghdad City.

TABLE III. Validation and generalization result.

Classes	N_{P1}	N_{P2}	T_C	P_{TC}	F_C	P_{FC}
Water	26006	27239	26006	2%	1233	1%
Residential(non contain Vegetation	512900	520455	512900	49%	7555	1%
Vegetation	115187	115187	115187	11%	0	0%
Residential(contain Vegetation	253054	253054	253054	24%	0	0%
Open Land	128549	128549	128549	12%	0	0%

The final results from the Research and experiment are use the coding and artificial networks can reach the results of classification up to 99%, but use of the method of supervised training in BPNN is imperative for us use pre-classified images using other systems ready to extract the training data and this makes us always need images classified as a reference for training, As a future work, suggest that use unsupervised training methods in artificial neural networks to overcome this obstacle.

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