An Automatic Neural Networks System for Classifying Dust, Clouds, Water, and Vegetation from Red Sea Area

G.M. Behery *behery2911961@yahoo.com*
Faculty of science, Math.and Comp. Department
Damietta University
New Damietta, 34517, Egypt.

Abstract

This paper presents an automatic remotely sensed system that is designed to classify dust, clouds, water and vegetation features from red sea area. Thus provides the system to make the test and classification process without retraining again. This system can rebuild the architecture of the neural network (NN) according to a linear combination among the number of epochs, the number of neurons, training functions, activation functions, and the number of hidden layers. Theproposed system is trained on the features of the provided images using 13 training functions, and is designed to find the best networks that has the ability to have the best classification on data is not included in the training data.This system shows an excellent classification of test data that is collected from the training data. The performances of the best three training functionsare%99.82, %99.64 and %99.28for test data that is not included in the training data.Although, the proposed system was trained on data selected only from one image, this system shows correctly classification of the features in the all images. The designed system can be carried out on remotely sensed images for classifying other features.This system was applied on several sub-images to classify the specified features. The correct performance of classifying the features from the sub-images was calculated by applying the proposed system on some small sections that were selected from contiguous areas contained the features.

Keywords: NNs , Image Processing, Classification, Dust, Clouds, Water, Vegetation.

1. INTRODUCTION

Remote sensing images provide a general reflection of the spatial characteristics for ground objects. Extraction of land-cover map information from multispectral or hyperspectral remotely sensed images is one of the important tasks of remote sensing technology [1-3]. Precise information about the landuse and land cover changes of the Earth's surface is extremely important for any kind of sustainable development program [4, 5].In order to automatically generate such landuse map from remotely sensed images, various pattern recognition techniques like classification and clustering can be adopted [6, 7]. These images are used in many applications e.g. for detecting the change in ground cover [8-10], extraction of forest [11-13], and many others [14-16].

NN algorithms are widely used for classifying features from remotely sensed images [17, 18].NN offers a number of advantages over conventional statistical classifiers such as the maximum likelihood classifier. Perhaps the most important characteristic of NN is that there is no underlying assumption about the distribution of data. Furthermore, it is easy to use data from different sources in the NN classification procedure to improve the accuracy of the classification. NN algorithms have some handicaps related in particular to the long training time requirement and finding the most efficient network structure. Large networks take a long time to learn the data whilst small networks may become trapped into a local minimum and may not learn from the training data. The structure of the network has a direct effect on training time and classification accuracy. The NN architecture which gives the best result for a particular problem can only be determined experimentally. Unfortunately, there is currently no available direct method developed for this purpose [19, 20]. The NN algorithms are always iterative, designed to step by step minimise the difference between the actual output vector of the network and the desired output vector. The Backpropagation (BP) algorithm is effective method for classifying features from images [21, 22].

The following training functions are chosen as classifiers in the proposed system. They are Resilient Propagation (trainrp) [23, 26, 34-37], Gradient descent (traingd) [38], Gradient descent with momentum (traingdm) [38], Scaled conjugate gradient (trainscg) [39], Levenberg-Marquardt (trainlm) [40], Random order incremental training with learning functions (trainr) [41], Bayesian regularization (trainbr) [41], One step secant (trainoss) [42], Gradient descent with momentumand adaptive learning rule (traingdx) [43-44], Gradient descent with adaptive learning rule (traingda) [45], Fletcher-Powell conjugate gradient (traincgf) [38, 46], Polak-Ribiére conjugate gradient (traincgp)[46], and Batch training with weight and bias learning rules (trainb)[47] backpropagation algorithms.

This work is usedNN for classifying dust, clouds, water and vegetation features from red sea area. BP is the most widely used algorithm for supervised learning with multi-layered feed-forward networks and it is very well known, while the trainrpfunction is not well known. The trainrpfunctionis faster than all the other BP functions[27-30]. The rest of paper is organized as follows; Section 2 describes the pattern data that is used for training and testing the system. Section 3 presents the proposed system. Section 4 shows the obtained results. Finally, Section5 concludes the work.

2. PATTERN DATA

This study is carried out on three images that were obtained by the Moderate Resolution Imaging Spectroradiometer(MODIS) on NASA's Aqua satellite. The first image contains multiple dust plumes blew eastward across the Red Sea. Along the eastern edge of the Red Sea, some of the dust forms wave patterns. Over the Arabian Peninsula, clouds fringe the eastern edge of a giant veil of dust. East of the clouds, skies are clear. Along the African coast, some of the smaller, linear plumes in the south may have arisen from sediments near the shore, especially the plumes originating in southern Sudan. The wide, opaque plume in the north, however, may have arisen farther inland, perhaps from sand seas in the Sahara [31]; see figure(1). The second one has dust plumes blew off the coast of Africa and over the Red Sea. The dust blowing off the coast of Sudan is thick enough to completely hide the land and water surface below, but the thickest dust stops short of reaching Saudi Arabia. Farther south, between Eritrea and Yemen, a thin dusty haze hangs over the Red Sea [32]; see figure (2). The third contains dust plumes blew off the coast of Sudan and across the Red Sea. Two distinct plumes arise not far from the coast of Sudan and blow toward the northeast. The northern plume almost reaches Saudi Arabia. North of these plumes, a veil of dust with indistinct margins extends from Sudan most of the way across the water [33]; see figure (3). These three images are called image1, image2, and image3 respectively. They are RGB format and their information is shown in table (1).

In this study, the classification is specified for dust, clouds, water, and vegetation features. Each feature has approximately the same colour in the three images. So, the pattern data is selected randomly by sampling throughout the image2 only. Where, it contains all features clearly. The selection of this data is such that it contains samples of all features. The pattern data for each pixel consists of three pixel grey-levels, one for each band. These bands are red, green and blue. The grey levels in the original images are coded as eight bits binary numbers in the range from 0 to 255. In order to train the NNs, all pixels values are normalised to lie between 0.0 and 1.0. The pattern data is collected from the proposed image for the features: dust, clouds, water, and vegetation. After the collection, each feature is represented as one group. Each group is divided into two parts: two-thirds for training and one third for test. Then, the training groups are merged in single file, and the test groups in other file.

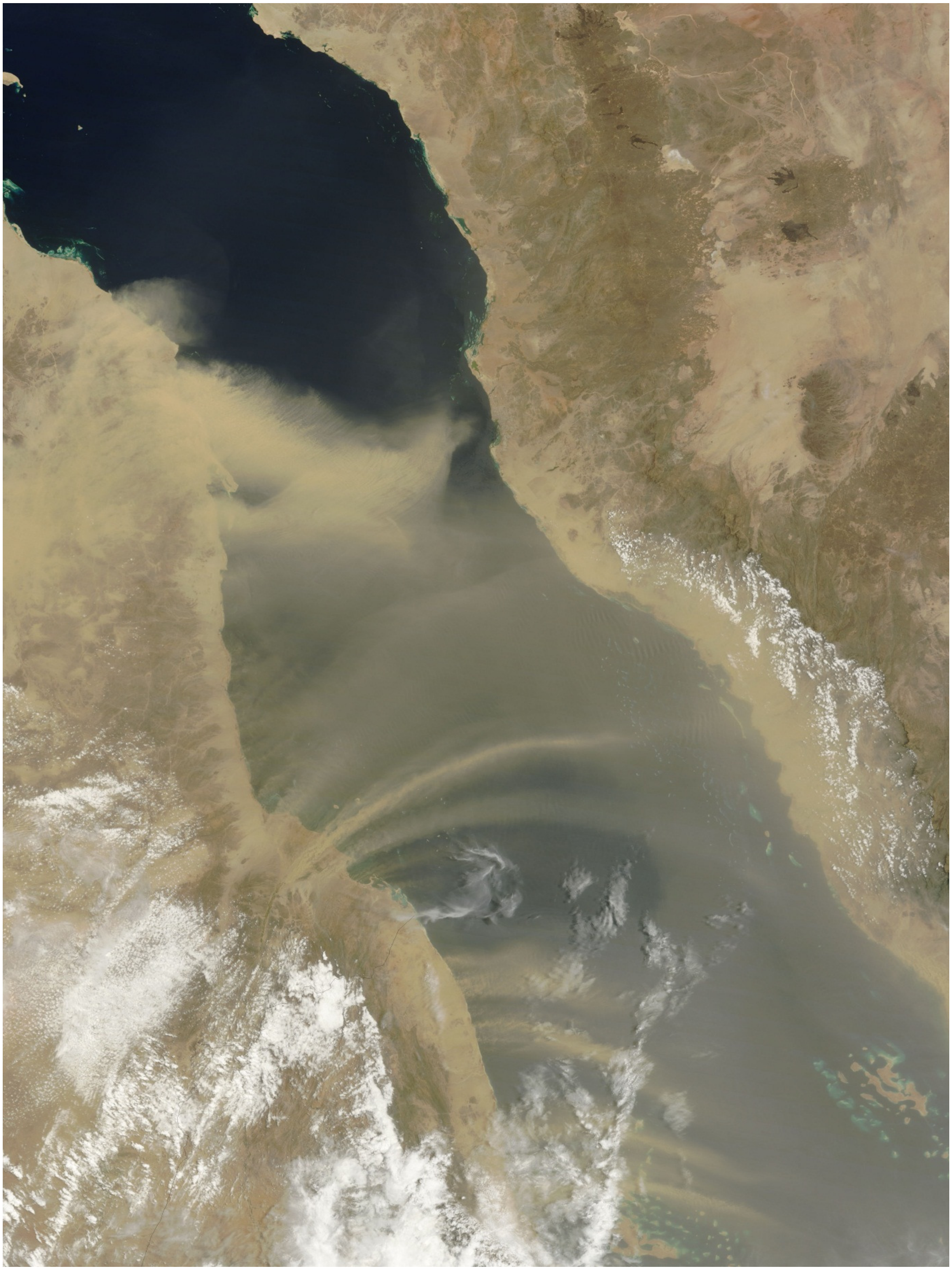


FIGURE 1: The first original image (image1) was taken by NASA Satellite.

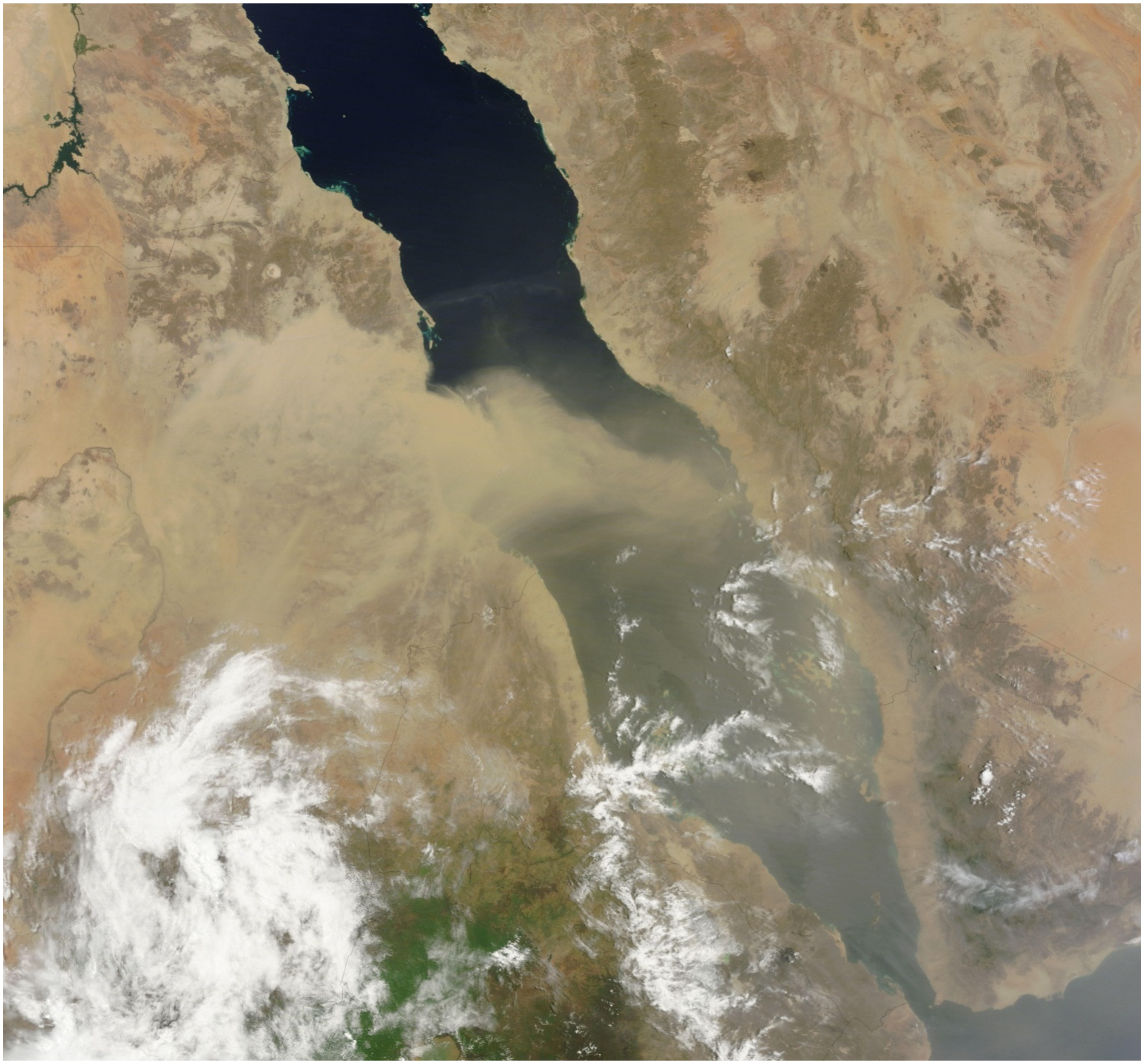


FIGURE 2: The second original image (image2) was taken by NASA Satellite.

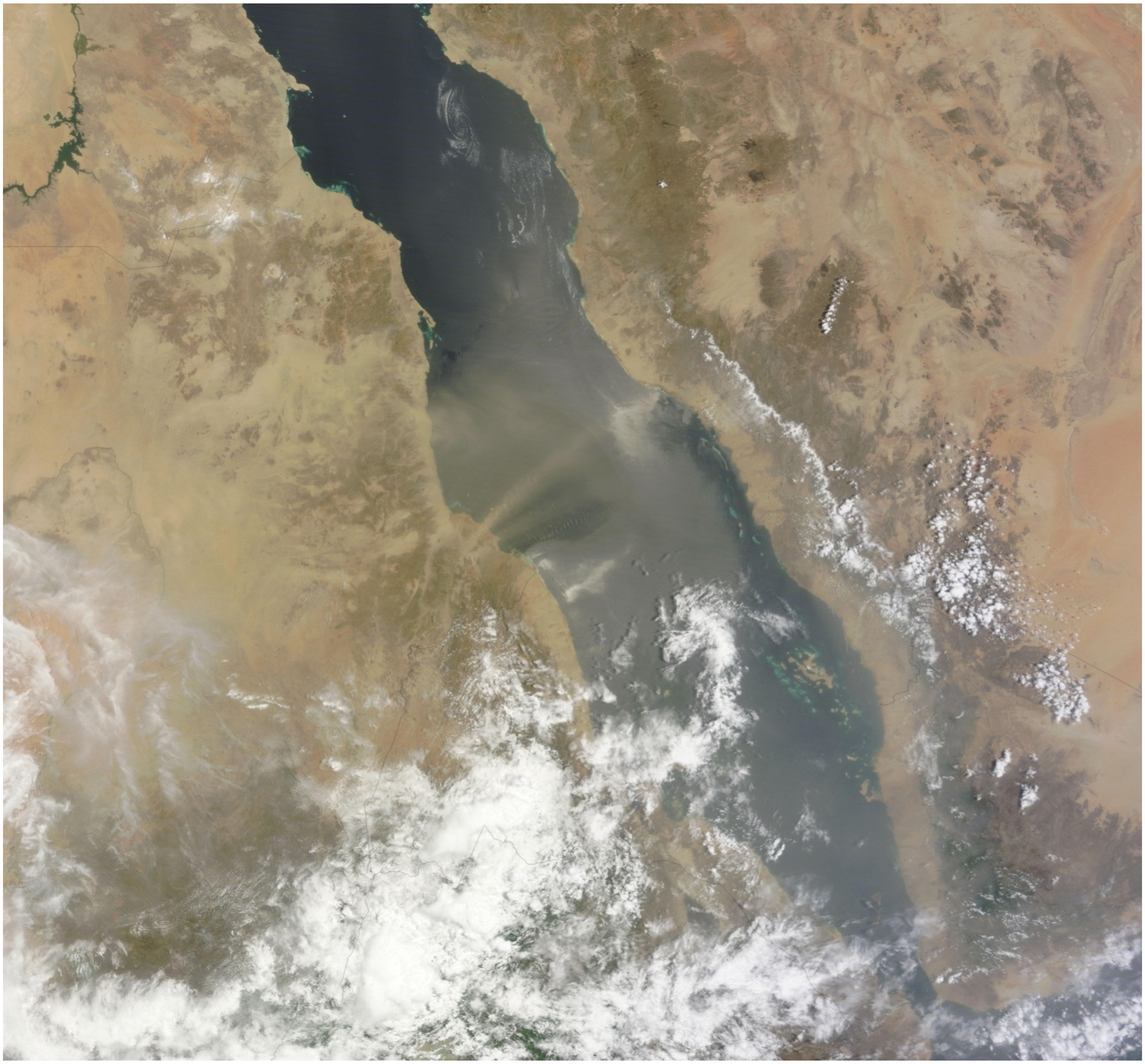


FIGURE 3: The third original image (image3) was taken by NASA Satellite.

Name	taken date	length	width	size /MB
image1	July 24, 2010	4000	2800	1.14
image2	mid-July 2011	5916	6372	3.14
image3	Aug. 3, 2011	5916	6372	3.25

TABLE 1: Information of the Studied Three Images.

3. PROPOSED SYSTEM

NNsare very effective methods to classify features fromimages. Figure (4)shows the NN architecture. This architectureconsists of input layer with R elements, two hidden layers with S neurons, and output layer with one element. The proposed system is designed to work in automatic way without any help from the user. The system is firstly started with building initial NN architecture without hidden layer by selecting the first training and activation functions from lists. Then, the initial number of neurons and epochs are specified.The weighted values are initialized randomly. After that, the system is trained and tested. If the required performance is reached, the resulted network is used for classifying the proposed features. Otherwise, this experiment is repeated again for ten times using the same system architecture of the NN hoping to get a random weighted values lead to improved performance. In the case ifthe required performance is not reached, the system rebuildsthe architecture of the NN according to a linear combination among the number of epochs, the number of neurons, training functions, activation functions, and the *number* of hidden layers. This system is illustrated in more details in the following algorithm and figures (5- 6).

1 - Preprocessing
- *Create a list of training functions names.*
- *Create a list of activation functions names.*
- *Specify the following components of NNs:*
    - *number of hidden layers*
    - *number of neurons for each layer*
    - *number of epochs*
    - *training function name.*
    - *activating function name.*
    - *experment_counter = 0.*

2- Build NN architecture.

3- Initialize weight values randomly.

4- Train the system.

5- If the required performance (Training and test) reached go to step 8

6- If the experment_counter< 10 then experment_counter++ and go to step 3

7- Create a new system architecture by specifying linear combination of the following:
- *increase the number of neurons per layer*
- *increase the number of Epochs*
- *select a new training function from the list*
- *select a new activation function from the list*
- *increase the number of hidden layer*

go to step 3.

8- Saves the workspace.

9- Call the classification process to extract features of partial images; see figure (6)

10- Prints the results system and keep it in the files.

11- Stop.

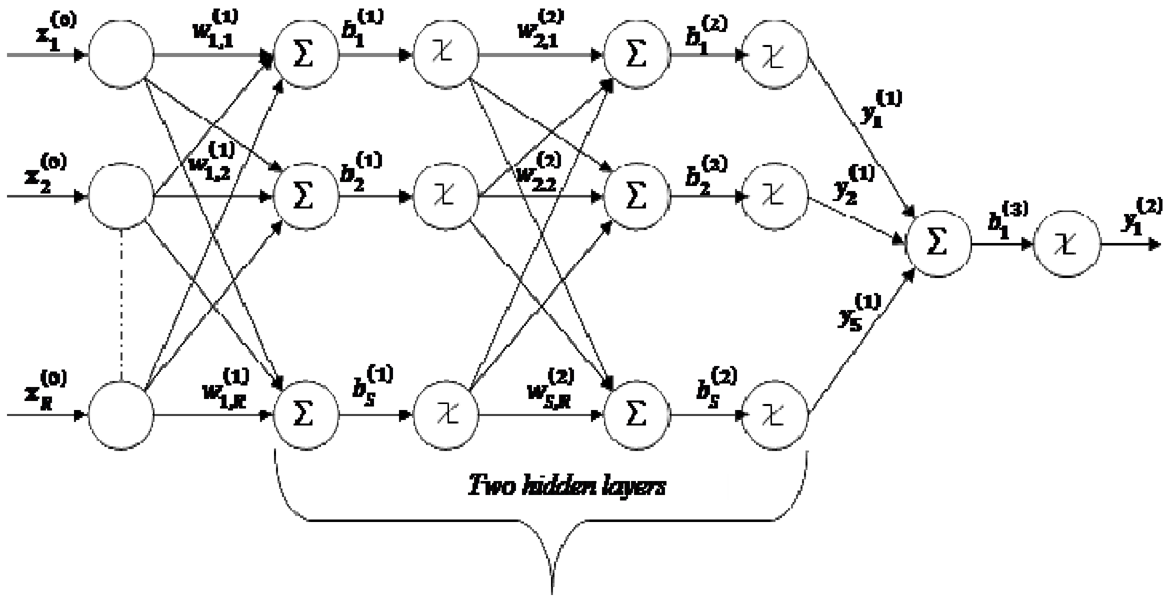


FIGURE 4: Network Architecture using Two Hidden Layers.

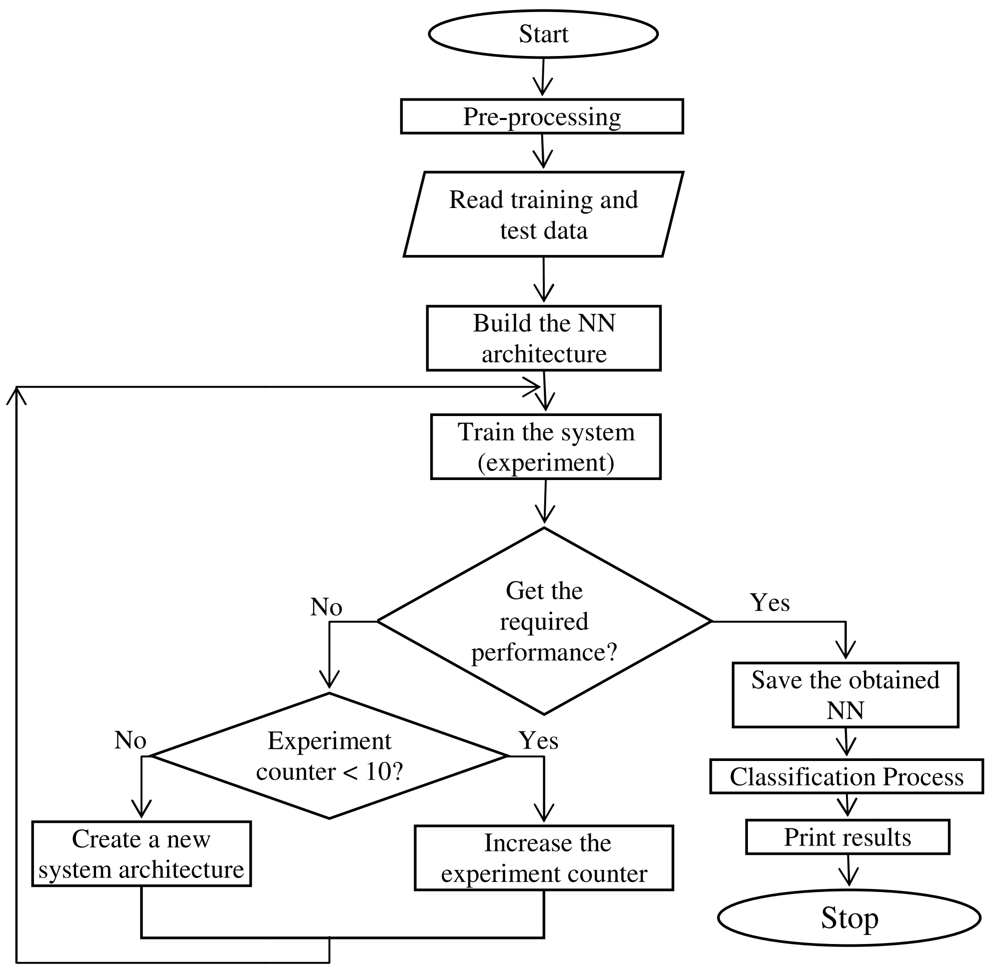


FIGURE 5: Flowchart for the Proposed System.

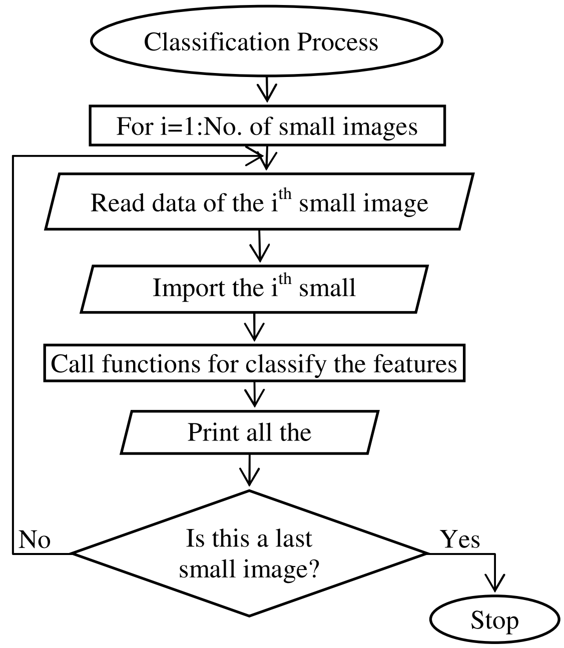


FIGURE 6: Flowchart for the Proposed Classification Process.

4. RESULTS

The proposed system wasapplied and simulated on the selected data; this data was3348 examples for training and 1116 examples for testingas specified in the Section (2). The system is carried out on a set of training functions to make a comparison among them. It was found that, two hidden layers with 33 and 11 neurons are enough for reaching the optimal solution. After the training, the obtained performances for training and test data are listed in table (2) and shown in figure (7). It was noticed that the best three training functions are trainbr, trainlm and trainrp and their performances are presented in figure (8). Moreover, the obtained best networks of these functions are reached at 2965, 645, and 20000 epochs. For each layer, W and b represent the weights and the biases respectively. The architectures of these training functions are given in figure (9). The linear regression between the network outputs and targets are introduced in figure (10).

Threesections are chosen from the studied three images for classifying features; one sections from each image. The information of these sections is introduced in table (3).This system was prepared to form pattern data for thesesections to classify dust, cloud, water and vegetation features from their pixels. Thesesections were selected from area containing the specified features.The best networks of the three training functionswere classified the features data from the specified sections precisely.Figures (11-13) show the selected threesections and their NN classification results respectively.

In order to calculate the correct performance of these networks for classifying or mis-classifying features data,four small sections were selected from contiguous areas containedthe specified features.One section for each feature is chosenfrom the three images, except the vegetation feature is not found in contiguous area in the image1 and image3. Figure (14) shows a sample of these features taken from image2. The coordinates of these sections are given in table (4). The best networkswere applied on these sections to classify their pixels as specified features. It was found that the performance of the proposed system was working in powerful process; see table (4).

In order to evaluate the proposed system, a comparison amongthis system and others is presented in table (5). This comparison shows that the proposed system has the best accuracy.

Fn_name	trainrp	trainlm	trainb	trainbr	traincgf	traincgp	traingd	traingda	traingdm	traingdx	trainoss	trainr	trainscg
Epochs	20000	645	1000	2965	1000	1000	1000	1000	1000	1000	1000	1000	1000
Tr. Pr.	99.73	100	99.64	100	99.37	99.46	99.64	99.91	99.28	100	99.64	99.91	99.64
Ts. Pr.	99.28	99.64	95.97	99.82	98.93	99.27	95.25	97.22	93.01	95.88	98.21	99.01	99.19

TABLE 2: Comparative performance of different training algorithms for proposed system.

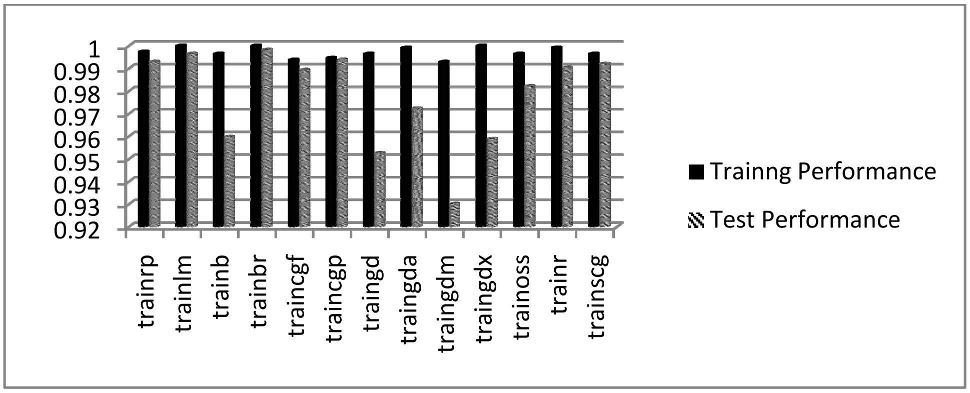
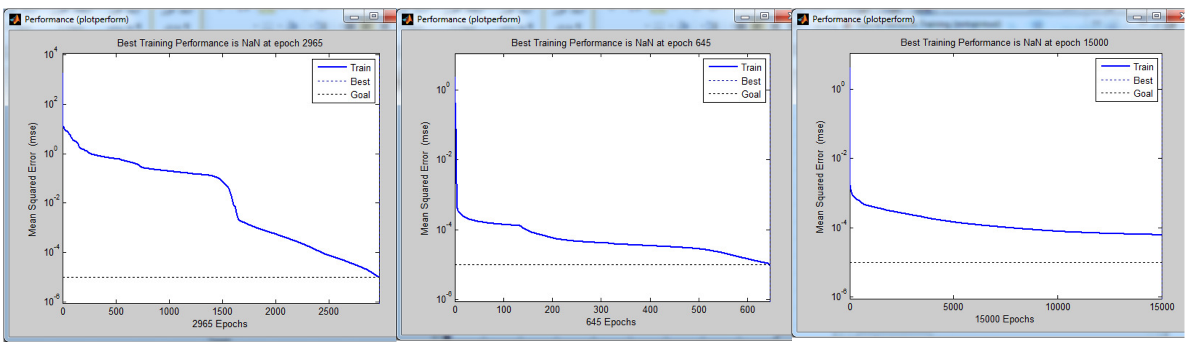
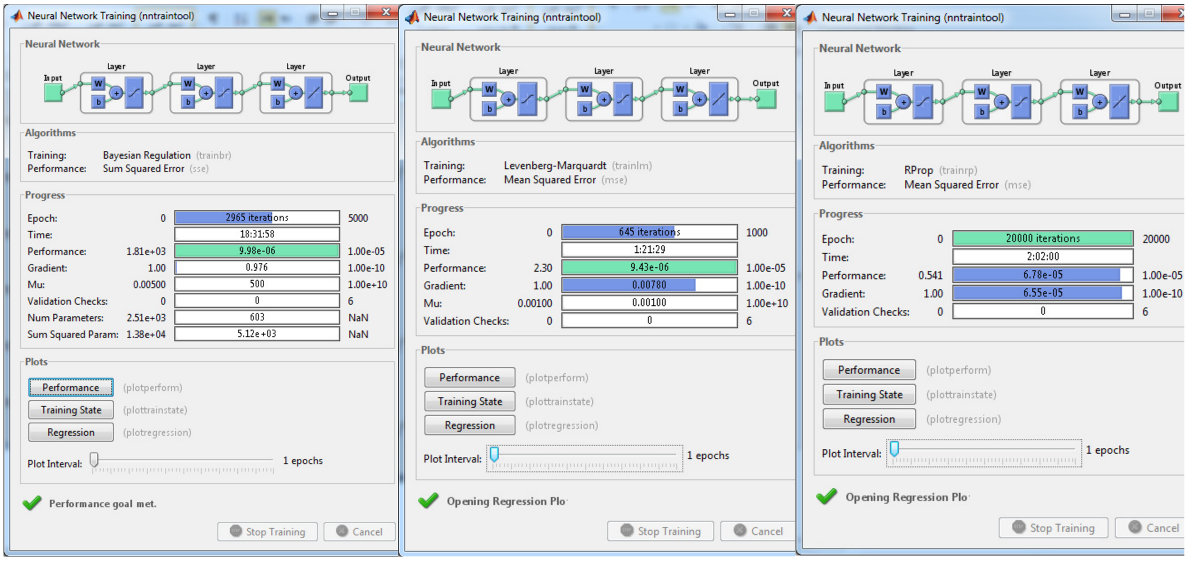


FIGURE 7: The Performances on Training and Test Data.



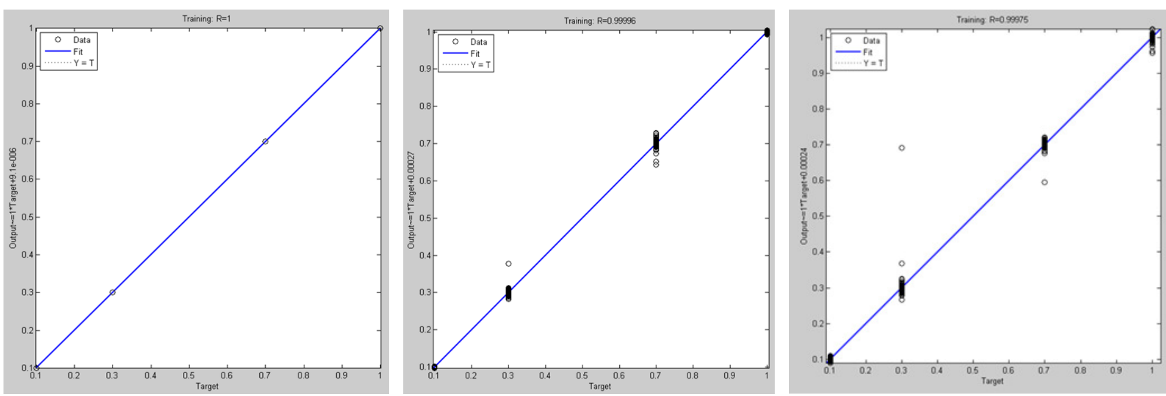
a) Trainbr b) Trainlm c) Trainrp

FIGURE 8: The NN Performance.



a) Trainbr b) Trainlm c) trainrp

FIGURE 9: The Architecture of the Best Network.



a) Trainbr b) Trainlm c) trainrp

FIGURE 10: Linear Regression Between The Network Outputs and Targets.

Taken from	Sections Coordinates
image1	2900x300
image2	3210x530
image3	1900x2200

TABLE 3: The Classified Sections Information.

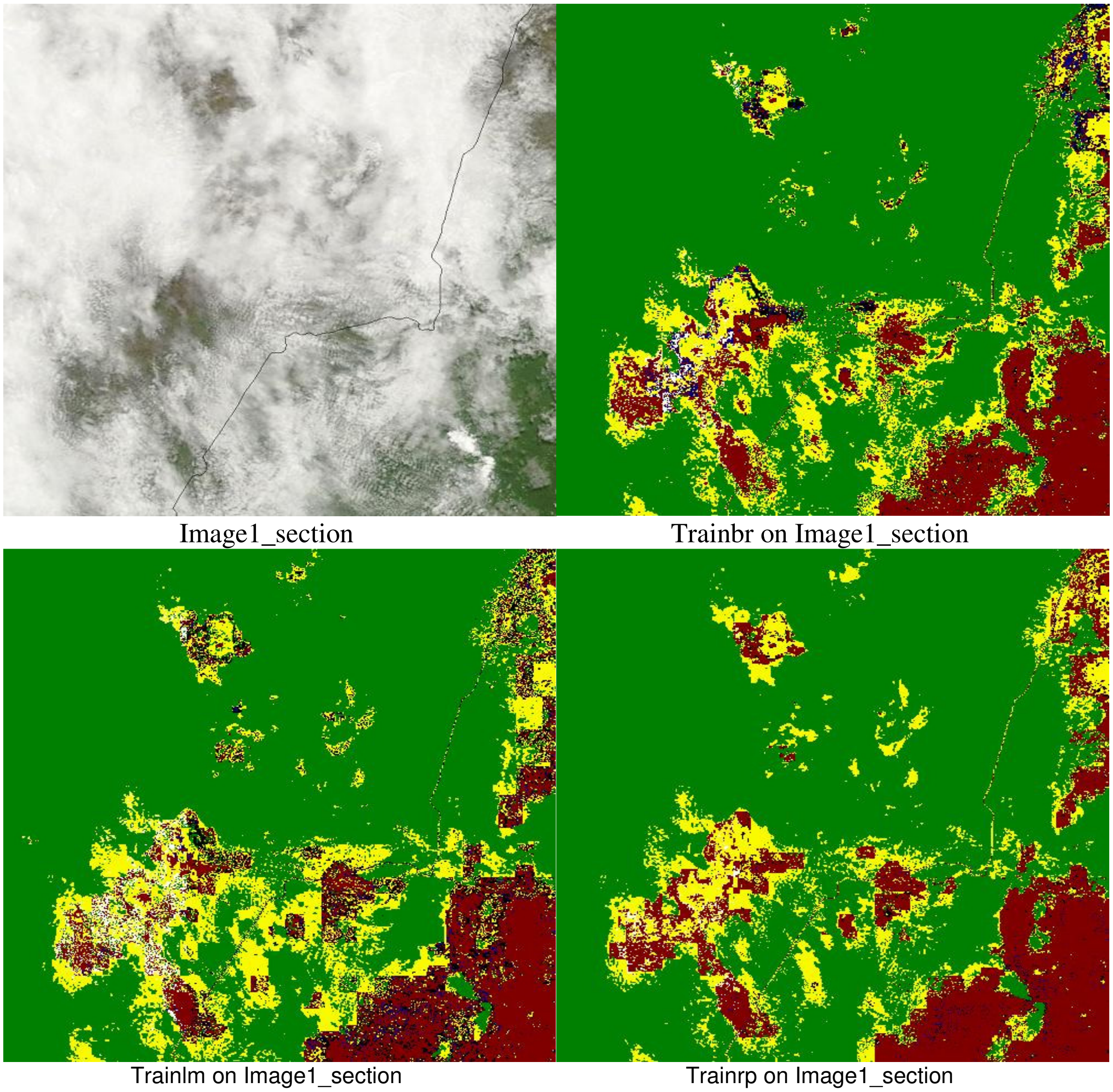


FIGURE 11: The NN lassification results of two sections taken from image1.

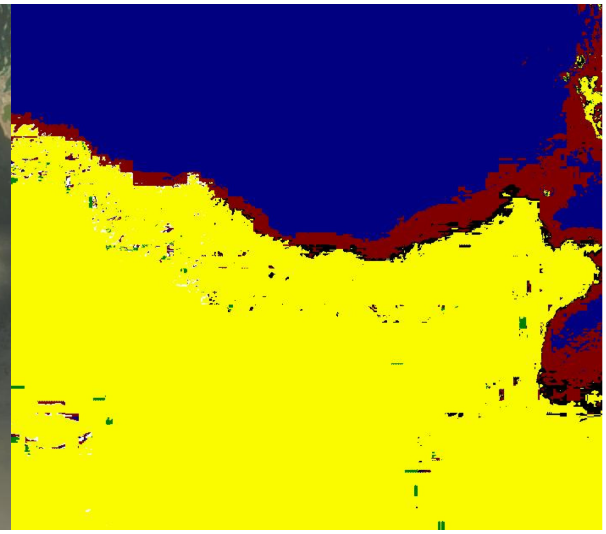
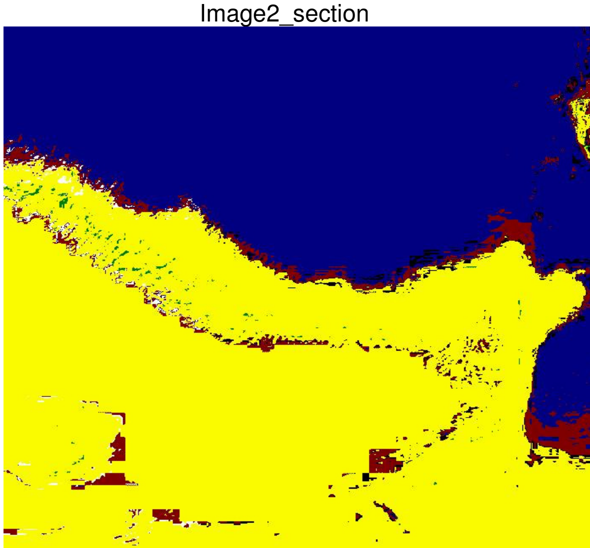
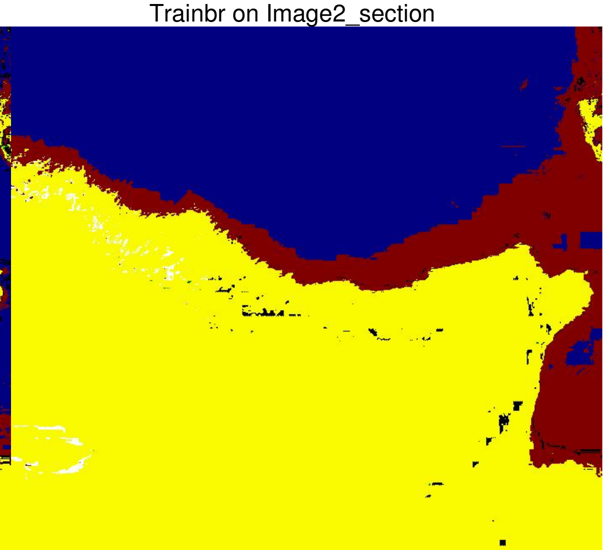



Image2_section   Trainbr on Image2_section

Trainlm on Image2_section   Trainrp on Image2_section

FIGURE 12: The NN classification results of two sections taken from image2.

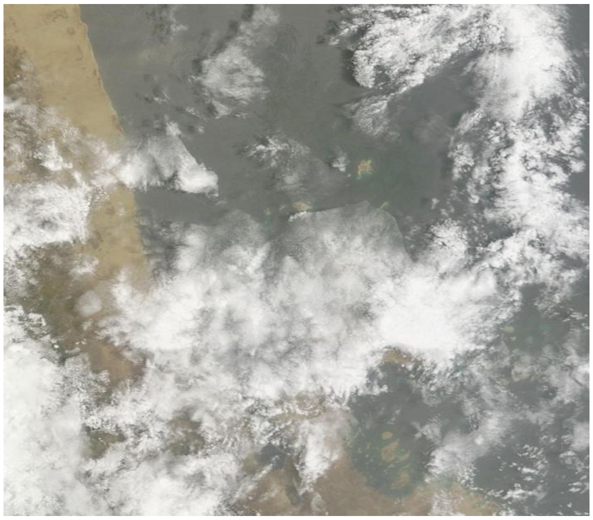
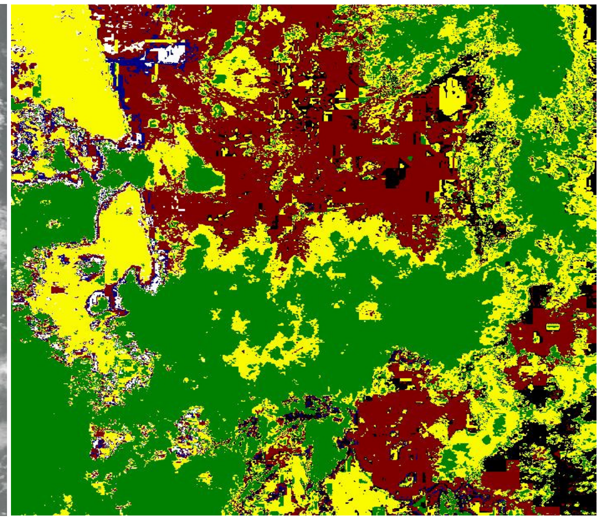
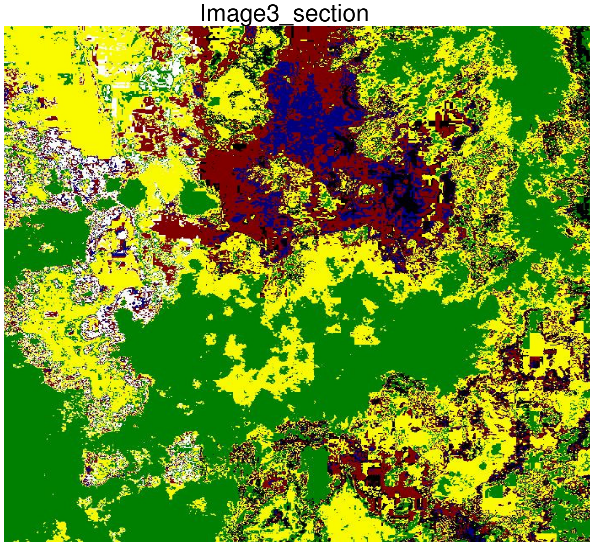


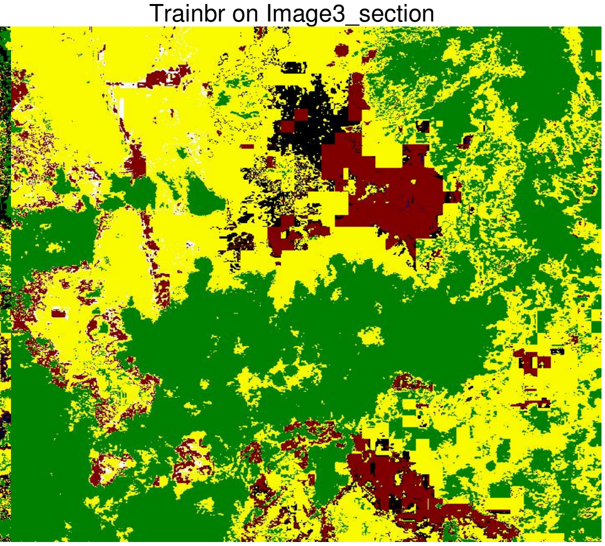
Image3_section



Trainbr on Image3_section



Trainlm on Image3_section

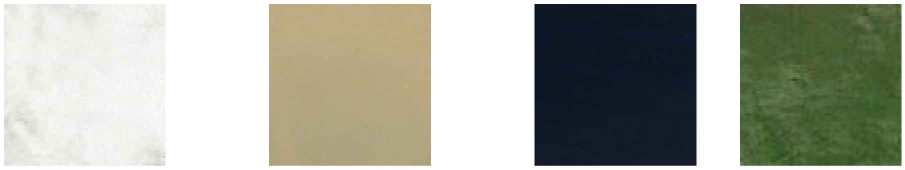


Trainrp on Image3_section

Figure 13:The NN classification results of two sections taken from image3.

Taken from	Sections coordinates and performance percent				
	Coordinates &Fun.Name	**dust**	**clouds**	**water**	**vegetation**
Image1	Coordinates	450x1270	1150x3930	260x130	---
	trainbr	%100	%100	%100	---
	trainlm	%100	%100	%100	---
	trainrp	%99.38	%100	%100	---
Image2	Coordinates	1500x1500	400x2750	1350x350	1360x3360
	trainbr	%100	%100	%100	%100
	trainlm	%100	%100	%100	%99.89
	trainrp	%100	%100	%100	%99.94
Image3	Coordinates	520x1660	1280x3320	1150x40	---
	trainbr	%100	%100	%100	---
	trainlm	%100	%100	%100	---
	trainrp	%99.69	%100	%100	---

TABLE 4: The System Performances of Classified Features.



Cloud Dust Water Vegetation

Figure 14: Test Images of Classified Features.

systems	Proposed system	[17, 24]	[48]	[49]	[50]
accuracy	% 99.82	% 99.6	% 94.06	% 92.34	% 90.8

TABLE 5: Comparison between the proposed systems and others.

5.CONCLUSION

This paper presents remotely sensed system that has the ability to classify dust, clouds, water and vegetation features from red sea area. This system was designed to work in automatic way for finding the best network. The proposed systemdid many tries to find the best networksusing low number of hidden layers and neurons. It was found that, two hidden layers with 33 and 11 neurons are enough for reaching the optimal solution.The performances of the best three training functions (trainbr, trainlm and trainrp) on the test data were %99.82, %99.64, and %99.28 respectively. Although, the proposed system was trained on data selected only from the image2,thissystem shows an excellent classificationofall features in the other two images. Moreover, the proposed system can simulate the other distributions not presented in the training set and matched them effectively.The system can store the obtained networks including the weighted and biases values. Thus provides the system to make the test and classification process without retraining again.

In order to calculate the classification performance of the best network on the features data, the proposed system was applied on some small sections that were selected from contiguous areas contained the specified features. The best networkswere applied on these sections, it was found that the proposed system was classified the clouds and water features from the three images correctly. It was noticed that the system was classified the dust feature correctly from the image2 that was used for collecting the training data. While,the other two images had some pixels that were mis-classified.

6. FUTURE WORK

This system can be improved with decreasing processing time of training by using the weighting values for previous experiment as initial weighting values for the next experiment.

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