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An efficient artificial neural network for Identification of Volcano Hotspots using Satellite Images

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ABSTRACT
Remote Sensing has gone to an extent of taking the geospatial accuracy to few centimeters. Currently remote sensing has become a tool in the hands of scientific community to develop modeling applied in the projection right from natural disasters. The use of remote sensing within the domain of natural hazards and disasters has become increasingly common, due in part to increased awareness of environmental issues such as climate change, but also to the increase in geospatial technologies and the ability to provide up-to-date imagery to the public through the media and internet. Here, the identification of volcanoes and their hotspot identification are important to protect the living things. Hence, the present investigation is utilized to identify the volcanoes and their hotspot from the satellite images. Therefore to overcome the aforesaid problems we are going to identify the hotspot of volcano using the Artificial Neural Network (ANN) which uses Resilient Back Propagation (RBP) Algorithm. At first, the color space of the satellite image will be converted to another color space to identify the contents of the image clearly. Then, the image will be segmented to identify the volcano's hotspot. Here we are going to use two stage hidden layers in neural network and to improve the accuracy we are going to more parameters for feature selection such as standard deviation, eccentricity, orientation, perimeter, entropy, mean, variance, contrast, homogeneity, energy, correlation. The proposed mechanism will be developed with the aid of the platform MATLAB (version 7.11).

KEYWORDS:

INTRODUCTION

The explosive growth of remote sensing technology, internet and multimedia systems poses great challenge in handling huge amount of data [5]. Advancement in the field of Remote Sensing has gone to an extent of taking the geospatial accuracy to few centimeters. Currently remote sensing has become a tool in the hands of scientific community to develop modeling applied in the projection right from natural disasters [4]. With the rapid development in remote sensing, digital image processing becomes an important tool for quantitative and statistical interpretation of remotely sensed images [3].

The use of remote sensing within the domain of natural hazards and disasters has become increasingly common, due in part to increased awareness of environmental issues such as climate change, but also to the increase in geospatial technologies and the ability to provide up-to-date imagery to the public through the media and internet [11]. One of the advantages of remote sensing is that the measurements can be performed from a great distance (several hundred or even several thousand kilometers in the case of satellite sensors), which means that large areas on ground can be covered easily. With satellite instruments it is also possible to observe, a target repeatedly; in some cases every day or even several times per day [12].

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Nowadays, satellite imaging [6] is one of the most important sources of geographical, geophysical and environmental information [1]. Satellite images [7] are important source of information which is used in many environmental assessments and monitoring of agriculture, meteorology etc. [2]. They are important available data sources for map generation and updating of available maps. They provide accurate easily accessible and reliable spatial information for Geographical Information Systems [9]. The advanced technology where most satellite images are recorded in digital format virtually, all image interpretation and analysis involve some elements of digital processing [11]. Increasing use of satellite images which are remotely sensed images acquired periodically by satellites on different areas and for multiple purposes makes it extremely interesting for various applications [8].

2. Related Researches: A Review:

A handful of researches are available and some of them are listed below. MirnalineeDhinesh*et al.* [12] have presented a multi-resolution based framework for detecting curvilinear structures from satellite images. Curvilinear structure detection finds its application in remote-sensed images for the extraction of networks such as roads, rivers, and highways. In the proposed methodology, curvilinear segments from the satellite images were extracted using multi-resolution GMM approach. The extracted curvilinear segments can be used for the detection and recognition of roads in the satellite images. Results have been showed the validity of the approach.

DebasishChakraborty*et al.* [13] have discussed that the texture in high-resolution satellite images requires substantial amendment in the conventional segmentation algorithms. A measure has been proposed to compute the Holder exponent (HE) to assess the roughness or smoothness around each pixel of the image. The localized singularity information is incorporated in computing the HE. An optimum window size is evaluated so that HE reacts to localized singularity. A two-step iterative procedure for clustering the transformed HE image is adapted to identify the range of HE, densely occupied in the kernel and to partition Holder exponents into a cluster that matches with the range. Holder exponent values (noise or not associated with the other cluster) are clubbed to a nearest possible cluster using the local maximum likelihood analysis

Shwetank et al. [14] have discussed that the Digital image processing is collection of techniques for the manipulation of digital images by computer and its applications. This collection of methods in remote sensing is dominantly treated as Satellite Digital Image Processing (SDIP). A space borne Multispectral Image Processing System (MIPS) has been used since 1960 as a traditional satellite image processing system for data analysis and extraction of meaningful information from/in the earth surface. The MIPS system provides limited information due to the small number of spectral channels. Over the past two decades, advances in satellite imaginary system have made it possible for the collection of several hundred spectral bands for processing. This is commonly referred to as hyper spectral Image Processing System (HIPS). Their study detailed the differences between MISP and HISP; and focused on the application of HIS for Rice crop-classification, plant growth, plant biophysical, biochemical, physiology properties in different spectral regions and their mapping.

Mohamed Awad [2] have discussed that the image segmentation is an essential step in image processing. The goal of segmentation is to simplify and/or to change the representation of an image into a form easier to analyze. Many image segmentation methods are available but most of these methods are not suitable for satellite images and they require a priori knowledge. In order to overcome these obstacles, a proposed technique in satellite image segmentation method has been developed using an unsupervised artificial neural network method called Kohonen's self-organizing map and a threshold technique. Self-organizing map was used to organize pixels according to grey level values of multiple bands into groups then a threshold technique is used to cluster the image into disjoint regions that proposed technique is called TSOM. Experiments performed on two different satellite images confirm the stability, homogeneity, and the efficiency (speed wise) of TSOM method with comparison to the iterative self-organizing data analysis method. The stability and homogeneity of both methods are determined using a procedure selected from the functional model.

Ashok *et al.* [15] have presented a GUI based multi spectral image enhancement used to achieve highly realistic and geo-scientifically corrects visualizations of real satellite imagery quite often the useful data in a digital image populates only a small portion of the available range of digital values. Image enhancement involved changing the original values so that more of the available range is used; this then increases the contrast between features and their backgrounds. It consists of reading the binary image on the basis of pixels taking them byte wise and displaying it, calculating the statistics of an image, automatically enhancing the color of the image based on statistics calculation using algorithms and working with RGB color bands. Finally the enhanced image has been displayed along with image histogram.

3. Image Recognition using cascade stage ANN:

The present analysis is utilized to identify the volcanoes and their hotspot from the satellite images. Therefore to overcome the aforesaid problems we are going to identify the hotspot of volcano using the Artificial Neural Network (ANN) which uses Resilient Back Propagation (RBP) Algorithm [17]. These basically consist of inputs, which are multiplied by weights, and then computed by a mathematical function which determines the activation of the neuron and another function computes the output of the artificial neuron. The idea of the back propagation algorithm is to reduce the error (difference between actual and expected results), until the cascade stage ANN learns the training data

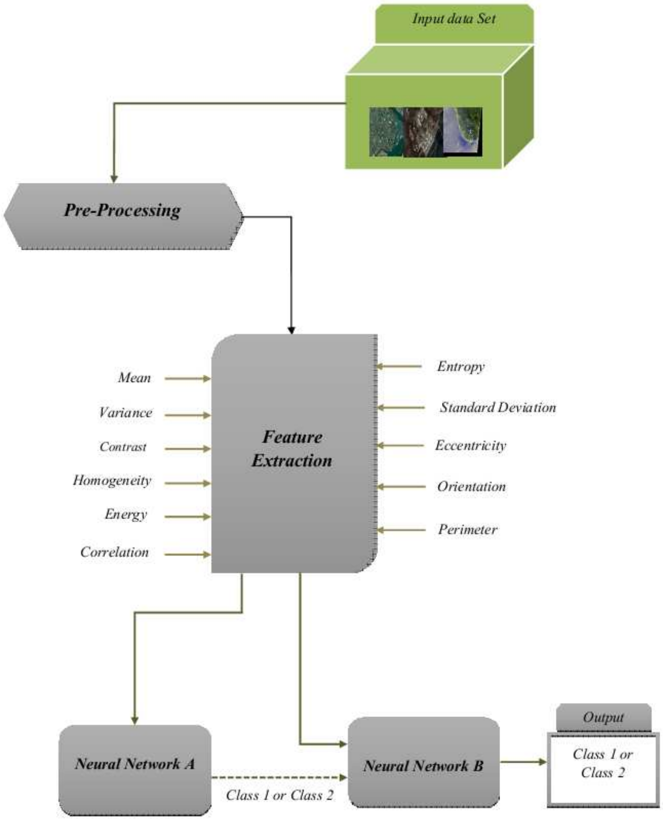

Fig. 1: Block Diagram of our proposed method

3.1. Feature Extraction:

Gray Level Co-Occurrence Matrix (GLCM) has proved to be a popular statistical method of extracting textural feature from images. According to co-occurrence matrix, Haralick defines fourteen textural features measured from the probability matrix to extract the characteristics of texture statistics of remote sensing images. In this work more important features are selected for implementation using

Area:

The simple shape descriptor used in the proposed method is the area. The area of a particular image can be calculated using the expression given below,

$$Area, A = \frac{I_h}{I_w} \tag{1}$$

Where,

I_h - Image height.

I_w - Image width

Perimeter:

P=2(Ih+IW)

Circularity:

The shape descriptor called circularity is the measure of perimeter to that of the area in an image which can be calculated using the expression given below,

$$Circularity, C = \frac{P^2}{A} \tag{2}$$

Where,
A - Area
P - Perimeter, which is measured by,

$$P = 2\prod\sqrt{((I_w/2)^2 + (I_h/2)^2)/2} \tag{3}$$

Auto Correlation:

Correlation measures the linear dependency of grey levels of neighboring pixels. Digital Image Correlation is an optical method that employs the changes in images. This is often used to measure deformation, displacement, strain and optical flow, one very common application is for measuring the motion of an optical mouse

$$A_c = \frac{\sum_i \sum_j (i,j)\,p(i,j) - \mu_i \mu_j}{\sigma_x \sigma_y} \tag{4}$$

Contrasts:

Contrast indicates the variance of the gray level. It is the difference between the highest and the lowest values of a set of pixels. GLCM contrast tends to be highly correlated with spatial frequencies

$$C = \sum_{n=0}^{N_t-1} n^2 \{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)\}, |i-j| = n \tag{5}$$

Cluster Prominence:

$$CP = \sum_{i,j} ((i-\mu_i)+(j-\mu_j))^4 P(i,j) \tag{6}$$

Cluster Shade:

$$CS = \sum_{i,j} ((i-\mu_i)+(j-\mu_j))^3 P(i,j) \tag{7}$$

Dissimilarity:

$$Dis = \sum_{i,j} |i-j| P(i,j) \tag{8}$$

Homogeneity:

$$Hom = \sum_{i,j} \frac{P(i,j)}{[1+(i-j)]} \tag{9}$$

Energy:

Angular Second Moment is also known as Uniformity or Energy. It is the sum of squares of entries in the GLCM Angular Second Moment measures the image homogeneity. Angular Second Moment is high when image has very good homogeneity or when pixels are very similar

$$Energy = \sum_{i,j} P(i,j)^2 \tag{10}$$

Entropy:

This parameter measures the disorder of an image. When the image is not textually uniform many GLCM elements have very small values, which implies that entropy is very large.

$$Ent = \sum_{i,j} P(i,j)\log(P(i,j)) \tag{11}$$

$$\text{Mean } (\sigma_M) = \sum_{i,j} x(i,j)/n \tag{12}$$

$$\text{Variance } (\sigma_v) = \frac{\sum x(i,j)^2}{n} \tag{13}$$

$$Std.Deviation = \sum_{i,j=0}^{N-1} (P_{x,y}(i,j) - \mu_{x,y}(i,j))^2 \tag{14}$$

3.2. Artificial Neural Network:

(M_1 ….. M_{11})- The 11 Features that we extracted are given as input to the neural network to proceed. (H_{a1} H_{a2} ……… H_{a20}) - The hidden layers in neural network a (H_{b1} H_{b2} ………. H_{b20}) - The hidden layers in neural network b. Y_n - The Output that defines class 1 or class 2

Neural networks are also known as artificial neutral network. For modeling and design of antenna recently neural network computational modules have got acceptance as an unorthodox and useful tool. neural networks (NN) have been used to the structure and the functionality of biological nature of human brain. Therefore, cascade stage ANN is found to be more flexible and apposite than other modeling methods [26].

The ANN consists of three layers: input, output and hidden layer. They are composed of a series of computational node structured into several layers. Each node is connected to all the nodes in the previous layer.

The input pattern is presented to the input layer of the network. These inputs are propagated through the network until they reach the output units. This forward pass produces the actual or predicted output pattern. Because back propagation is a supervised learning algorithm, the desiredoutputs are given as part of the training vector. The actual network outputs are subtracted from the desired outputs and an error signal is produced. This error signal is then the basis for the back propagation step, whereby the errors are passed back through the neural network by computing thecontribution of each hidden processing unit and deriving the corresponding adjustment needed to produce the correct output. The connection weights are then adjusted and the neural network has just "learned" from an experience. Once the network is trained, it will provide the desired output for any of the input patterns.

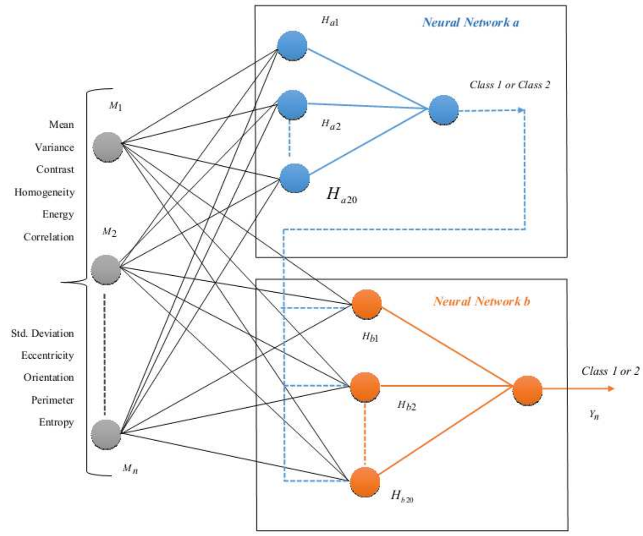

Fig. 2: Proposed Two stage Neural Network for Volcano Hotspot image classification

To create a network that can handle volcano images it is best to train the network in both satellite images and volcano images. To do this network will first be trained on satellite images until it has a least square. Then the network will be trained on 15 sets of satellite images and volcano images. The above parameters for the each satellite images in the database are found out using the above equations. Then the network will again be trained on just satellite images. This ensures that the network will respond perfectly when presented with a normal satellite image.

4. Experimental Setup:

In order to train neural network with two stages, selected 11 features were estimated.At first, the color space of the satellite image will be converted to another color space to identify the contents of the image clearly. After this process, the image will be segmented to identify the volcano's hotspot. After segmentation a randomly chosen sample was divided into training, validation and testing phases. Training the data set is to learn about the data in the network, Validation is used to measure the training performance.

RESULTS AND DISCUSSION

The proposed of ANN with cascade stage method is done by using MATLAB software version 2014a latest version in a system having 8 GB RAM with 32 bit operating system having i5 Processor. Here for finding the efficiency and accuracy we consider many parameters. Testing data set is consisting of 100 satellite images in which 50 volcano and 50 non volcano images. Testing is done under the evaluation of sensitivity and specificity values. These values are among the terms true positive (TP), true negative (TN), false positive (FP), false negative (FN). The example satellite images for the image processing for the identification of hotspot in the volcano images is shown below in detail

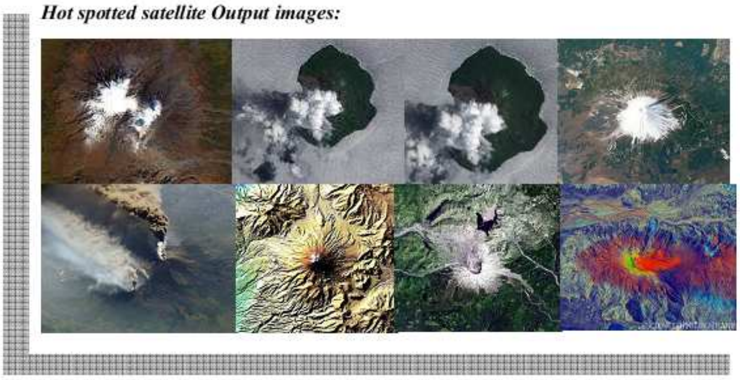

Fig. 4.1: Input Non-volcanic images and volcanic images

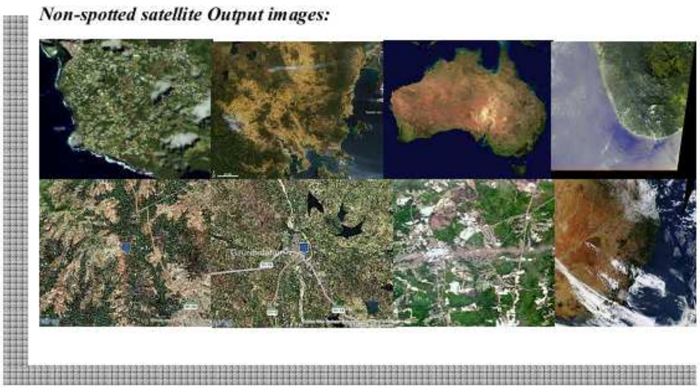

Fig. 4.2: Hot spotted Output Satellite Images

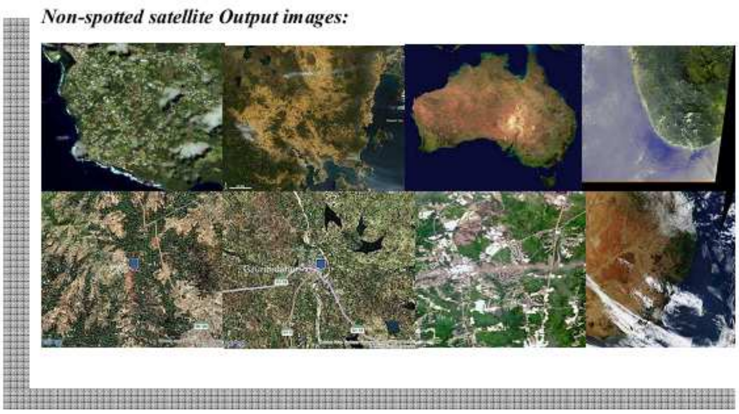

Fig. 4.3: Non- spotted Output Satellite Images

Table 1: Comparison for the Performance Analysis using Precision and recall

Performance Analysis			
Precision		Recall	
Proposed Method	Existing Method(16)	Proposed Method	Existing Method(16)
0.9375	0.8825	0.9	0.876

Table 2: Obtained values for evaluation metrics such as TP, TN, FP and FN

Evaluation Metrics	Obtained Values
True positive	45
True negative	47
False positive	3
False negative	5

Table 3: Obtained values from the Features parameter we used for extraction and neural network output in Non-volcanic Images

M	V	C	E1	P	O	E2	S	NN1	NN2
128.91	964.4199	797942	108.884	6086.1	2606.654	0	31.05	0.870	0.673
123.56	1041.982	826210	465.235	12156.1	9707.461	0.0007	32.27	1.255	1.224
112.14	1317.600	865143	427.074	8676.69	7129.838	0	36.29	1.150	1.160
126.80	924.8376	822084	543.793	14881.5	10819.14	0.0016	30.41	1.380	1.314
125.32	1047.526	827915	504.578	14283.0	11648.00	0	32.36	1.381	1.319
112.26	1029.611	842855	551.076	13124.6	11426.41	0.0003	32.08	1.396	1.343
108.80	1585.184	915669	513.091	8820.96	11090.65	0.0006	39.81	1.390	1.378
117.54	440.9857	797743	535.654	10670.1	12858.81	0	20.99	1.479	1.162
118.91	643.9021	771890	559.639	13491.0	8944.995	0	25.37	1.353	1.186
113.93	572.3075	853429	522.559	8456.01	12402.11	0	23.92	1.525	1.194

Where,
M-Mean, V-Variance, C-Contrast, H-Homogeneity,
E-Energy, C-correlation, E1-Eccentricity, P-Perimeter,
O-Orientation, E2-Entropy, S-Standard deviation,
NN1-Neural Network 1 and NN2-Neural Network.

Table 4: Obtained values from the Features parameter we used for extraction and neural network output in Volcanic Images

M	V	C	E1	P	O	E2	S	NN1	NN2
116.48	1439.3	10077	528.81	10181	11064.	0.0014	37.938	1.0595	0.8293
113.36	704.25	78595	544.54	11361	14256	0	26.537	0.8879	0.7546
118.70	837.77	77725	569.86	14026	12691	0	28.94	1.0126	0.9798
124.37	1311.6	76613	548.13	12612	13280.	0	36.216	1.0986	1.0502
132.47	836.55	90280	574.94	15541	10541	0.0037	28.923	1.4914	1.5489
140.34	3302.3	2.5406	574.54	13713	11371	0.0157	57.465	1.7504	2.2703
117.37	1076.5	1.51037	632.19	17181	9755.2	0.0020	32.810	1.6518	1.8480
122.39	831.22	71292	630.83	16090	6850.9	0.0001	28.830	1.6738	1.4678
146.61	1539.7	9.9719	937.12	27117	9278	0.0020	39.240	2.0719	2.3218
121.20	1537.9	2.0937	951.14	22725	7045	0	39.217	2.5562	1.9859

Where,
M-Mean, V-Variance, C-Contrast, H-Homogeneity,
E-Energy, C-correlation, E1-Eccentricity, P-Perimeter,
O-Orientation, E2-Entropy, S-Standard deviation,
NN1-Neural Network 1 and NN2-Neural Network.

Table 5: Parameter measures such as Accuracy, Sensitivity and Specificity for proposed ANN Two Stage technique.

Parameter Measures	Percentage (%)
Accuracy	92
Sensitivity	90
Specificity	94

The values of sensitivity, specificity, accuracy, positive prediction value, negative prediction value, false positive rate. Sensitivity is defined as the ability to identify the volcano images and it is 90%. The specificity, the ability to identify correctly the non-volcano images which yields 94%. Accuracy is the correct image recognition which is found as 92%. The false positive rate, which is recognized as an error, has result of 3%. Positive predictive value which is the proportion of the positive results has been identified as 92%. The false discovery rate which is the identification of false results and it is 5%. The Matthew's correlation coefficient has been used for the identification of the results, which hold its value from the range of -1 to +1. The value +1 concludes as a correct identification and vice versa. Hence it is concluded that volcano hotspot images can be easily identified by using ANN.

Conclusion:

Thus the mechanism to identify the volcano hotspot images using cascade stage Artificial Neural Network. The training and testing of the dataset satellite images is undergone using cross-validation and classification function (sensitivity and specificity measures) respectively. Results presented in this paper shows that red spotted in the volcano images is easily identified using cascade stage ANN mechanism. Even the results are encouraging image processing needed some special attention to improve the accuracy level where it is maximum of 92%.

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