HYPERSPECTRAL IMAGE VEGETATION CLASSIFICATION USING BACK PROPAGATION NEURAL NETWORK WITH OPTIMIZATION ALGORITHM

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Abstract--- There is numerous contributions in the literature for regions extraction, by fusing spectral and spatial information in land use classification problems. To improve the vegetation region new schemes are developed for ecological or land use applications. Multispectral sensing tenders a enormous amount of information for classification of vegetation regions. With the development of remote sensing technologies, researchers are optimistic towards addressing such problems. This paper presents a powerful tool in data dimensionality reduction of spectral images. In this paper automated tool of image processing techniques are used to classify the vegetation region into sixteen classes. The classification of vegetation region by Back Propagation Neural Network (BPNN) is employed in which the weighted value is optimized by swarm intelligence. The simulation results are evaluated by performance metrics and compared with existing methods. This method results in better accuracy than other classification results.

Keywords--- Hyper spectral Image, Remote Sensing, Back Propagation Neural Network and particle swarm optimization.

I. INTRODUCTION

Many researchers have investigated various methods to classify vegetation over earth surface[1]. A wide range of techniques have been developed to interpret land cover classes from remote sensing and satellite spectral images .There are large number of satellite sensors which provides hyper spectral images besides multispectral and panchromatic images. Hyper spectral information provides high knowledge to detect various classes in the image [4]. There have been many vegetation indices like NDVI (Normalized Difference Vegetation Indices), RVI (Ratio Vegetation Index), TVI (Transformed Vegetation Index), used in studies on crop estimation and vegetation growth.

Hyper spectral imaging collects and process information across the spectrum [7]. In this paper an automated tool to distinguish the land covers in remote sensed images has been investigated using back propagation neural network. It is relatively a new technology that is being investigated by researchers. However, it deals with imaging narrow bands which cover range from 500 to 700nm. Hyper spectral spectroscopy combines the power of digital imaging and spectroscopy. Due to the high dimensional the classification of regions is complicated task for researchers. We have built an automated back propagation network tool to classify the regions. Here in the neuron model the weights are optimized by intelligence of particles swarm.

In hyper spectral imaging, the spectra have fine wavelength resolution and cover a wide range of wavelengths. Hyper spectral image processing are used for applications in astronomy, agriculture [5], molecular biology, biomedical imaging, and surveillance. Objects in hyper spectral images leave signatures to identify the materials of the output classes. In general there are four ways for sensors to sample the three dimensional hyper spectral cube. They are spatial scanning, spectral scanning, and spatio-spectral scanning. The major factor apart from spectral resolution is spatial resolution. In spatial scanning, two dimensional outputs obtain slit spectra by projecting followed by dispersing with prism. In second type of scanning, two dimensional sensor output represents monochromatic map of the image. These are typical band pass filters. In the third type two dimensional sensor output represents wavelength coded map of the image.

To monitor the development and health of crops hyper spectral imaging classification and its limitations are discussed in Section II. Our proposed neural network methodology is discussed in the Section III.

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II. HYPERSPECTRAL CALSSIFICATION LITERATURE SURVEY

In general, high dimensionality data reduction is major issues in hyper spectral image classification. Assigning land covers to pixels can be done in remote sensing by three ways. They are supervised, unsupervised, and object-based image analysis. In Supervised way of classification the image is guided by the user to specify the land cover classes of interest. In Unsupervised way the image is processed without any guidance. Here by means of cluster analysis it is possible to explore the data to find hidden groups in data. In object based way, categorization of pixels is based on the spatial relationship with the surrounding pixels. This section presents the literature survey of remote sensing classification.

J.Li.J.M.Bioucas-Dias et al [2] presented a new method on combing hidden markov random field segmentation with support vector machine classifier. In Hidden markov model the system being modelled is assumed to be markov process with unobserved states. It is represented by dynamic Bayesian network. But the major limitation of this method is that it does not extract spatial information

E.Vansteenkiste [6] et al compared the power of classifying regions based on using colour information to use texture and color texture information. They found that color features perform best in the easy classification tasks. A very high classification rates are obtained using color texture features.

P.R.Marpu [4] et al presented extended attribute profiles as efficient tools for spectral-spatial classification of remote sensing images. This method was tested on two datasets and results found to be accurate. The drawback of this method is that it requires manual selection of parameters.

Z.Hu.Z.Wu, Q.Zhang, [8] et al presented a novel spatially constrained color texture model for hierarchical segmentation of very high resolution images. This starts with initial partition followed by features selection, and finally optimized region merging process. The limitation of this approach is distance calculations of each pair of adjacent regions are spatial constraint.

S.Bernabe [9] et al, proposed a a new strategies for spectral-spatial classification of remotely sensed data. This focus on possibility of performing advanced spectral-spatial classification with limited spectral resolution. Here, extended multiattribute profiles (EMAPs) built on the expanded set of spectral features.

III. BACK PROPAGATION NEURAL NETWORK METHODOLOGY

In this paper initially the input image is pre-processed by filter to remove the noise. Secondly, the features are extracted that contains the relevant information about the input image. Back Propagation Neural Network (BPNN) is used as a classifier to classify the multispectral vegetation image in which Dragonfly algorithm is used to optimize the weighted value in BPNN. Figure 1 shows the flowchart of proposed method Process

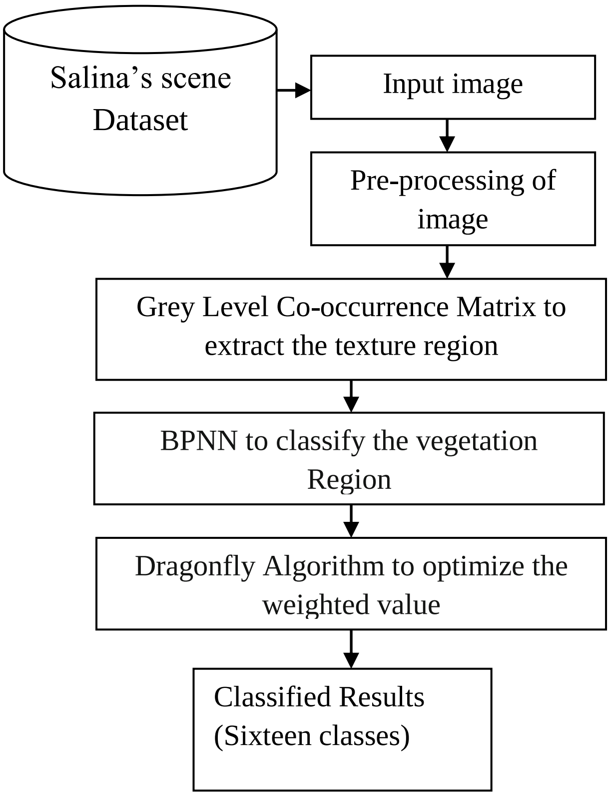

Figure 1 FLowchart for Proposed BPNN

Back Propagation Neural Network

One of the most popular NN algorithms is backpropagation algorithm. Back propagation is a training method used for a multi-layer neural network and also used for linear as well as non-linear classification. In this method, BPNN is used to classify the vegetation region into 16 classes. It is chosen because of high-speed classification and supports multiclass classification.

It is also called the generalized delta rule. It is a gradient descent method which minimizes the total squared error of the output computed by the net. BPNN is a supervised algorithm in which error difference between the desired output and calculated output is backpropagated. The procedure is repeated during learning to minimize the error by adjusting the weights thought the backpropagation of error. As a result of weight adjustments, hidden units set their weights to represent important features of the task domain. BPNN consists of three layers such as Input Layer, Hidden Layer, andOutput Layer. A number of the hidden layers and number of hidden units in each hidden layers depend upon the complexity of the problem. The Learning algorithm of BPNN is to 3 steps

- Feed forward of the input pattern
- Calculation and Backpropagation of the associated error
- Adjustments of the weight

After the neural network is trained, the neural network has to compute the feed forward phase only. Even if the training is slow, the trained net can produce its output immediately. A multilayer neural network with one layer of hidden units is shown in figure 2.

The output units and the hidden units can have biases. These bias terms are like weights on connections from units whose output is always 1. During feedforward, the signals flow in the forward direction i.e. from the input unit to hidden unit and finally to the output unit. During back propagation phase of learning, the signals flow in the reverse direction.

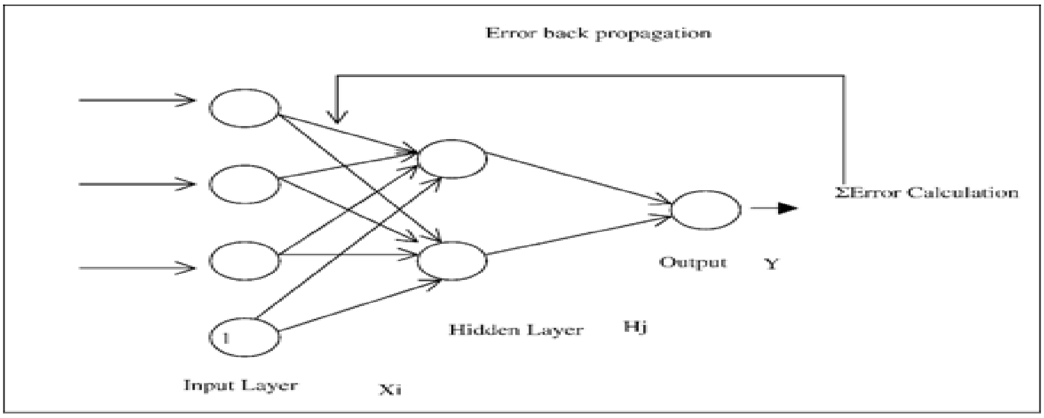

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Figure 2 Architecture of BPNN

During feed forward, the training pattern (vegetation region) is fed to the input layer (Xi) the weighted sum of the input to the j^{th} node in the hidden layer is given by

$$Net_j = \sum w_{ij} x_i + \theta_j \quad \text{---Equ (3)}$$

This equation is used to calculate the aggregate input to the neuron. The θ_j term is the weighted value from a bias node that always has an output value of 1.

The input unit $x_i$receives an input signal and sends this signal to each of the hidden units Z_1, Z_2, …Z_n. Each hidden unit computes its activation and sends its signal to each output unit. Each output unit computes its activation to compute the output or the response of the neural net for the given input pattern.

The Pseudocode for BPNN is given below:

```
Assign all network inputs and output
Initialize all weights with small random
numbers, typically between -1 and 1
repeat
    for every pattern in the training set
    //      Propagated the input forward
through the network:
            for each layer in the network  and for
every node
                    1. Calculate the weight sum of the
inputs to the node
                    2. Add the threshold to the sum
                    3. Calculate the activation for the
node
                end
            end
//      Propagate the errors backward through
the network
            for every node in the output layer
                calculate the error signal
            end
            for all hidden layers
                for every node in the layer
                    1. Calculate the node's signal
error
                    2. Update each node's weight in
the network
                end
            end
//      Calculate Global Error
            Calculate the Error Function
    end
while ((maximum  number of iterations < than
specified) AND
        (Error Function is > than specified))
```

During training, each output unit compares its computed activation k, with its target value t to determine the associated error for the particular pattern. Based on this error the factor ∂k for all m values are computed which is used to propagate the error at the output unit back to all units in the hidden layer. At a later stage, it is also used for updating of weights between the output and the hidden layer.

The values of ∂j are not sent back to the input units but are used to update the weights between the hidden layer and the input layer. Once all the ∂ factors are known, the weights for all layers are changed simultaneously. The adjustment to all weights wjk is based on the factor ∂k and the activation $z_j$of the hidden unit Z_j. The change in weight to the connection between the input layer and the hidden layer is based on ∂j and the activation x_i of the input unit.

Dragonfly Algorithm

The main motivation of the DA algorithm begins from the static and the dynamic swarming behaviors of dragonflies. The two swarming behaviours are very similar to the two key stages of optimization through metaheuristic algorithms, namely, exploration and exploitation. In the static swarm, dragonflies form sub-swarms and these fly over the different areas, which is the main purpose of exploration stage.

The behavior of dragonflies can be summarised as the combination of five steps, namely, Separation, Alignment, Cohesion, Attraction towards a food source and Distraction outwards an enemy

The separation is estimated as

$$D_i = \sum_j^N Y - Y_j$$

Where Y shows the position of the current individual, Y_j is the position of the j th neighbouring individual, Nis number of the neighbouring individuals.

The Alignment is estimated as

$$D_i = \frac{\sum_j^N Y_j}{N}$$

Where,Y_j shows the velocity of j^{th} nneighbouring individual.

Cohesion estimated as

$$D_i = \frac{\sum_j^N Y_j}{N} - X$$

Attraction towards food source is estimated as

$$A_i = Y^+ - Y$$

Where, Y and Y+ show the position of the current individual and that of the food source, respectively. Distraction outwards an enemy is estimated as

$$D_i = Y^- + Y$$

Where Y and Y^- are the position of the current individual and of the enemy, respectively. The position of the dragonflies is updated in the search space. In the final Phase, Food source and the enemy are selected from best and the worst solutions obtained in the whole swarm at any instant. This leads the convergence towards the promising regions of search space and at the same time, it leads divergence outward the non-promising areas in search space.

The obtained best solution is indicated as accurate weight value and used in the training algorithm for BPNN. The output results of BPNN as the classification of the vegetation region as 16 classes. The performance of BPNN with dragonfly is evaluated by certain parameters to calculate the classification accuracy.

IV. EXPERIMENTAL RESULTS

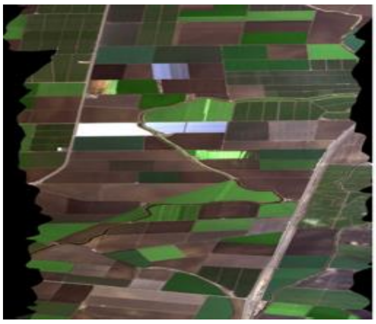
The performance of proposed method Back Propagation Neural Network with Dragon fly algorithm is developed to classify the multispectral satellite vegetation region into 16 class. The proposed method is compared with the existing Improved Relevance Vector Machine with Mosquito Flying Optimization (IRVM-MFO), Support Vector Machine (SVM) to evaluate the classification accuracy.

Salinas Dataset Description

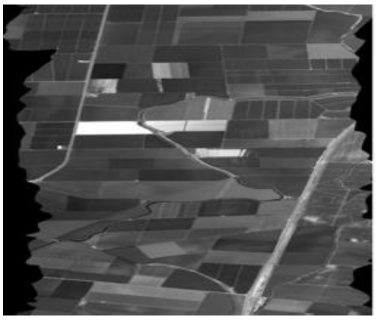
This scene was collected by the 224-band AVIRIS Sensor over Salinas's valley, California. It is characterised by high spatial resolution of 3.7 m pixels. The area covered comprises 512 lines by 217 samples. **Table1** below list the number of classes with samples.

Table 1 Number of classes with Samples

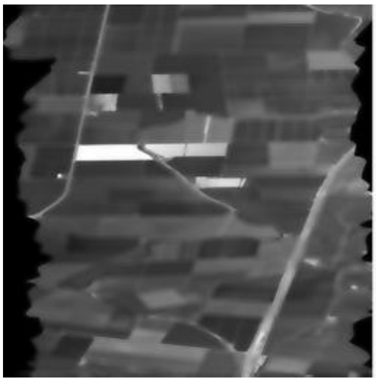
No	Class	Samples
1	Brocoli_green_weeds_1	2009
2	Brocoli_green_weeds_2	3726
3	Fallow	1976
4	Fallow_rough_plow	1394
5	Fallow_smooth	2678
6	Stubble	3959
7	Celery	3579
8	Grapes_untrained	11271
9	Soil_vinyard_develop	6203
10	Corn_senesced_green_weeds	3278
11	Lettuce_romaine_4wk	1068
12	Lettuce_romaine_5wk	1927
13	Lettuce_romaine_6wk	916
14	Lettuce_romaine_7wk	1070
15	Vinyard_untrained	7268
16	Vinyard_	



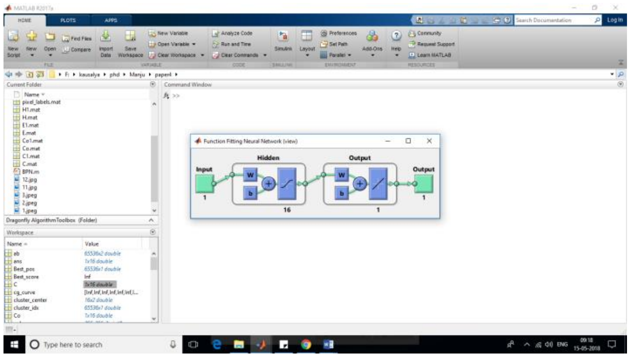
(a). Input image



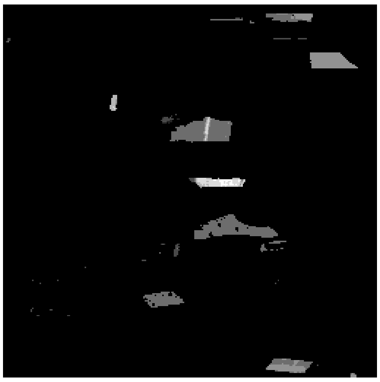
(b). GrayScale image



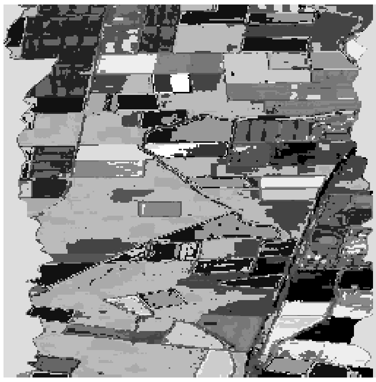
(c). Filtered image



(e). BPNN



(d). GLCM features of 16th class of input Image



(f). Classified Image

Figure shows the input image of vegetation region and the implemented process of the proposed method BPNN-DF

Table 2 shows the comparative analysis of performance metrics for the vegetation classification based proposed BPNN-DF algorithm. The proposed method is compared with existing methods to evaluate the classification accuracy in terms of accuracy, specificity, and sensitivity.

Table 2 Comparative Analysis of the Proposed BPNN-DF

Performance measures	BPNN-DF	IRVM-MFO	RVM	SVM
Accuracy	95.3	92.3	91.1	90.5
Sensitivity	93.2	90.1	88.9	87.89
Specificity	90.1	88.3	87.5	86.5

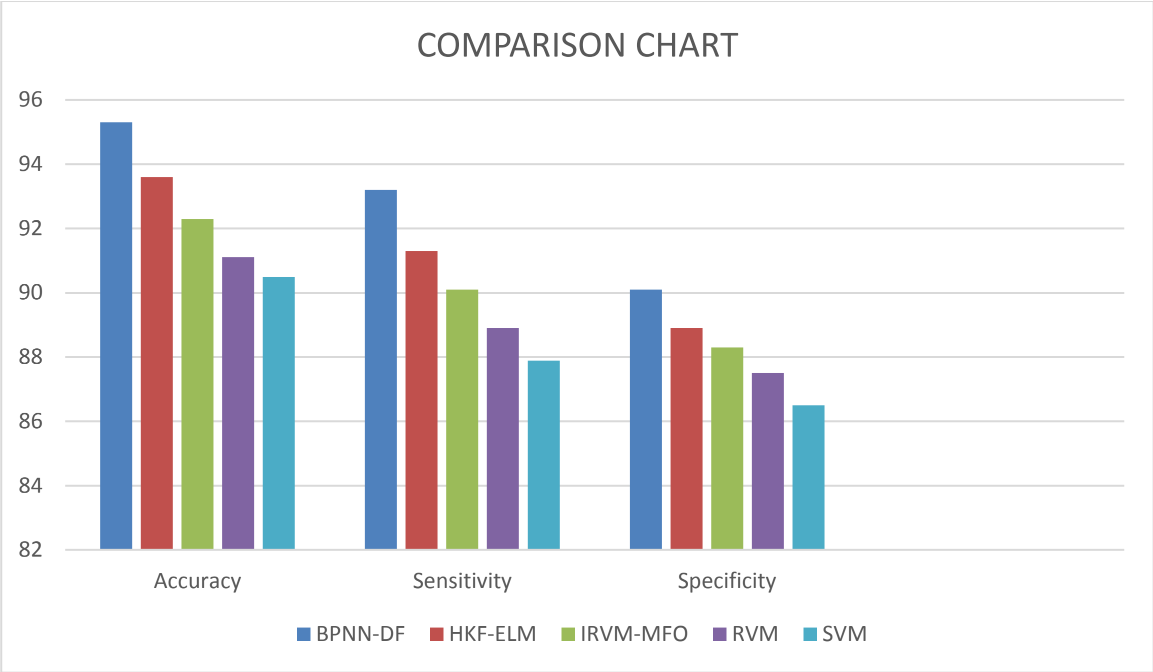


Figure shows the comparative analysis of accuracy, specificity and sensitivity evaluation of proposed method and exiting methods.

V. CONCLUSION

In this paper, we developed a new method for remote sensing image classification. The classification of vegetation region is important to improve the agricultural growth which is possible by automated tool of the image processing techniques. The input image undergoes pre-processing, feature extraction and classification by Back Propagation Neural Network in which the weighted value is optimized by Dragonfly algorithm is implemented. The experimental results are evaluated in terms of accuracy, sensitivity, and specificity. The proposed BPNN with DF achieves the efficient classification accuracy with less computation time. In our future work we plan to use hybrid neuron model with swarm optimization to achieve better classification.

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