REMOTE ASSESSMENT AND CHANGE DETECTION IN GREENLAI USING DIFFERENT VEGETATION INDICES

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KEY WORDS:

Fuzzy C-Means clustering (FCM), neural network, Levenberg-Marquardt (LM) algorithm, vegetation indices.

ABSTRACT:

Cotton crop identification based on the timely information has significant advantage to the different implications of food, economic and environment. Due to the significant advantages, the accurate detection of cotton crop regions using supervised learning procedure is challenging problem in remote sensing. Here, classifiers on the direct image are played a major role but the results are not much satisfactorily. In order to further improve the effectiveness, variety of vegetation indices are proposed in the literature. But, recently, the major challenge is to find the better vegetation indices for the cotton crop identification through the proposed methodology. Accordingly, fuzzy c-means clustering is combined with neural network algorithm, trained by Levenberg-Marquardt for cotton crop classification. To experiment the proposed method, five LISS-III satellite images was taken and the experimentation was done with six vegetation indices such as Simple Ratio, Normalized Difference Vegetation Index, Enhanced Vegetation Index, Green Atmospherically Resistant Vegetation Index, Wide-Dynamic Range Vegetation Index, Green Chlorophyll Index. Along with these indices, Green Leaf Area Index is also considered for investigation. From the research outcome, Green Atmospherically Resistant Vegetation Index outperformed with all other indices by reaching the average accuracy value of 95.21%.

1. INTRODUCTION

Remote sensing is the multipurpose tool intended for probing in to the vast expanse of this the Earth. In this regard, it includes the application of suitable equipments or sensors to “capture” the spectral and spatial relations of objects and materials visible at a far-off place. Aerial and satellite images, called remotely sensed images, pave the way for exact mapping of land cover and enable landscape traits furthermore comprehensible on provincial, continental, and even universal scales. It is widely engaged for the surveillance of the earth surface to assess the modifications in land utilization and land extent (Tansey, K. Chambers, I. Anstee, I. Denniss, A. Lamb, A., 2009). It is also profitably employed in the generation of mapping products for military and civil applications, assessment of ecological spoils, supervision of land utilization, radiation watch, town planning, development management, soil evaluation and crop yield assessment (James A. S. Daniel B. C., 2002). In addition, it finds itself widely applied for mapping and categorization of land extent traits such as vegetation, soil, water and forests and functions as an alternative for long-established techniques which carry out land extent categorization by means of costly and time-intensive field investigations (Govender, M. C. Naiken, V. Bulcock, H., 2008).
In crop yield evaluation, precise and prompt data on the locality and domain of key crop categories is bound to effectively exert monetary, food, policy, and ecological impacts. From times immemorial, remote sensing either singly or in conjunction with ground estimations has been widely applied in crop acreage analysis. While all dimensions of remotely sensed data are pertinent, it is the sequential data dimension that is most advantageous for locating main crop categories with remote sensing. The ostensible reason is that at any time in the course of the growing season, crops happen to be at diverse phases of maturity, and they are exhibited as differential levels of spectral reflectance in remotely sensed signals, thereby generating a crop-specific temporal record. Nevertheless, in spite of the elongated track record and the assurance of temporal supervision of crop categories, remote sensing has failed to come up to expectations by not being extensively functional in crop acreage evaluation (Ozdogan, M. Yang, Y. Allez, G. Cervantes C., 2010). However, the solitary crop class mining from coarser to medium remote sensing data has recently emerged as a daunting assignment. Therefore, it is highly essential to design a methodology and a technique for solitary crop class recognition from identical temporal images. Of late, investigations have reached an

advanced stage in computer vision techniques performed on remotely sensed images like segmentation, object-oriented and knowledge-based techniques for categorization of crop domains (Argialas, D. Harlow, C., 1990). Here, the research is taken into the direction of classifying the cotton crop regions using the computer vision methods as like (Musande, V. Kumar, A. Roy, P.S. Kale, K., 2013) (Jia, K. Wu, B. Li, Q., 2013) (Omar, M., 2011,) (Rajesh, K, D. Rajendra, Y. Kale, K.V. Mehrotra, S.C., 2013) (N. R. Rao, P. K. Garg, S. K. Ghosh,. 2007). The primary intention is to design and develop an approach for cotton crop classification of satellite images using FCM and neural network algorithm. The goal of this research is to provide the effectiveness in cotton crop classification of satellite images using the object-based image segmentation. Initially, the traditional vegetation indices will be applied and then FCM clustering will be chosen to segment the satellite images to segment the satellite images so that primitive objects of variable sizes and shapes can be obtained from the satellite images. Then, we will make use of neural network classifier to classify the pixels in satellite images using the segmented label with its neighbor's information obtained from the previous step. The paper is organized as follows: section 2 provides the motivation behind this work and section 3 presents the proposed methodology of the crop image classification. Section 4 elaborates the results and its investigation report with the suggestion. Section 5 concludes the paper.

2. MOTIVATION

Due to the necessity of understanding the cotton growth and expected cultivation for a specified time, the automated identification of cotton crop region has more influence among the researchers from the field of remote sensing. In olden days, segmentation techniques were applied to group the cotton crop regions and the success of applying the supervised algorithms to other fields forces the researched to do the same with satellite images. The application of supervised learning algorithm achieved good results recently. But, further improvement was satisfactorily achieved by applying those methods to different vegetation indices. These indices are well studied with different set of images to provide temporal indices data. To further improve the vegetation signal in remotely sensed data and present an estimated measure of green vegetation area, variety of spectral vegetation indices was developed by integrating data from multiple bands into single value. They associate with biophysical characteristics of the vegetation of the land cover. But, recently, the major challenge is to find the better vegetation indices for the cotton crop identification. The second challenge is to accurate detection of cotton crop regions using supervised learning procedure. These two challenges are taken into consideration and the solution is provided with fuzzy clustering and neural network as supervised procedure and the investigation with seven different indices.

2. PRAPOSED METHODOLOGY TO COTTON CROP CLASSIFICATION

This section presents the proposed crop image classification system using FCM clustering and Neural network. The effectiveness of the classification is achieved by combining the fuzzy-based segmentation with the learning-based neural classifier. Both the techniques are very effectives in their process, especially in remote sensing images. The adapting of both the techniques to do cotton crop identification needs a sequence of steps which are explained in four different processes. The flow chart of the proposed methodology is given in figure 1. The overall four different steps of the proposed methodology are given as follows: 1) Reading and Band computation of multispectral image, 2) Computation of vegetation indices and leaf area index, 3) Crop image segmentation through FCM clustering, and 4) Crop image classification through neural network.

3.1 Reading and Band computation of multispectral image

The first step of the proposed system is to read the LISS-III images which are kept as four different bands such as, R, G, NIR and SWIR band. The LISS-III images are stored as hdr format which is one of the standard formats of storing multiple spectral bands of satellite images. Here, the MATLAB syntax, called "multiband read" is used to read the image which gives four different bands sequentially as mentioned above. Another one band important for multispectral image processing is "B" band which is computed as per the following formulae,

$$B = 0.75R - 0.25G \quad (1)$$

Where, R→ R band of the input multispectral image G→ G band of the input multispectral image.

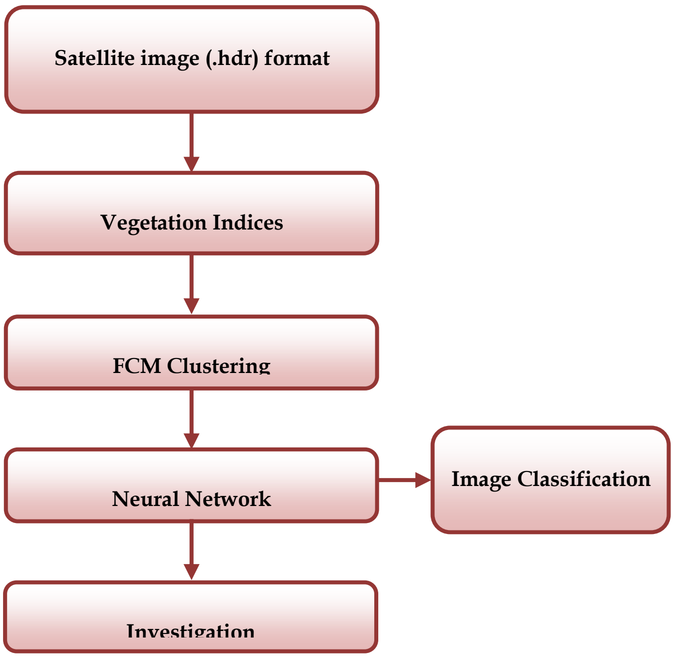


Figure. 1. Flow diagram of the proposed methodology

3.2 Computation of vegetation indices and leaf area index

Once five different bands are computed from the input multispectral images, six different vegetation indices and Green Leaf Index are computed. The sequent steps of this steps i given in figure 2. The intention of finding the vegetation indices are to analyze the performance of the proposed methodology over these different indices and the suggestion of the best band for cotton crop classification. These vegetation indices are taken from the literature, proposed by different authors to easily classify the vegetation area. The six different vegetation indices taken for investigation (Vina, A. Anatoly, A. G. Anthony, L. Nguy, R., Yi, P., 2011.) (Musande, V. Kumar, A. Kale, K., 2012.) are Simple Ratio (SR) (Jordan, C. F., 1969.), Normalized Difference Vegetation Index (NDVI) (Rouse, J. W., Haas, R. H., Jr., Schell, J. A., Deering, D. W., 1974.), Enhanced Vegetation Index (EVI) (Huete, A. R., Liu, H. Q., Batchily, K., vanLeeuwen, W., 1997), Green Atmospherically Resistant Vegetation Index (GARI) (Gitelson, A. A., Kaufman, Y. J., Merzlyak, M. N., 1996.), Wide Dynamic Range Vegetation Index (WDRVI) (Gitelson, A. A., Viña, A., Arkebauer, T. J., Rundquist, D. C., Keydan, G., Leavitt, B., 2003.), Green Chlorophyll Index (CI_{green}) (Gitelson, A. A., Viña, A., Ciganda, V., Rundquist, D. C., & Arkebauer, T. J., 2005.). Along with these indices, Green Leaf Area Index (GLAI) (Vina, A. Anatoly, A. G. Anthony, L. Nguy, R., Yi, P., 2011.) is also taken for investigating to find whether the taken index is suitable to do crop identification.

$$SR = \frac{NIR}{R} \tag{2}$$

$$NDVI = \frac{NIR - R}{NIR + R} \tag{3}$$

$$EVI = \frac{2.5(NIR - R)}{1 + NIR + 6 * R - 7.5B} \tag{4}$$

$$GARI = \frac{NIR - G - 0.9 * B - R}{NIR + G - 0.9 * B - R} \tag{5}$$

$$WDRVI = \frac{0.5(NIR - R)}{0.5(NIR + R)} \tag{6}$$

$$CI - Green = \frac{NIR}{G} - 1 \qquad (7)$$

$$CI - Green = \frac{NIR}{G} - 1 \qquad (8)$$

$$GLAI = 3.618 * EVI - 0.118 \qquad (9)$$

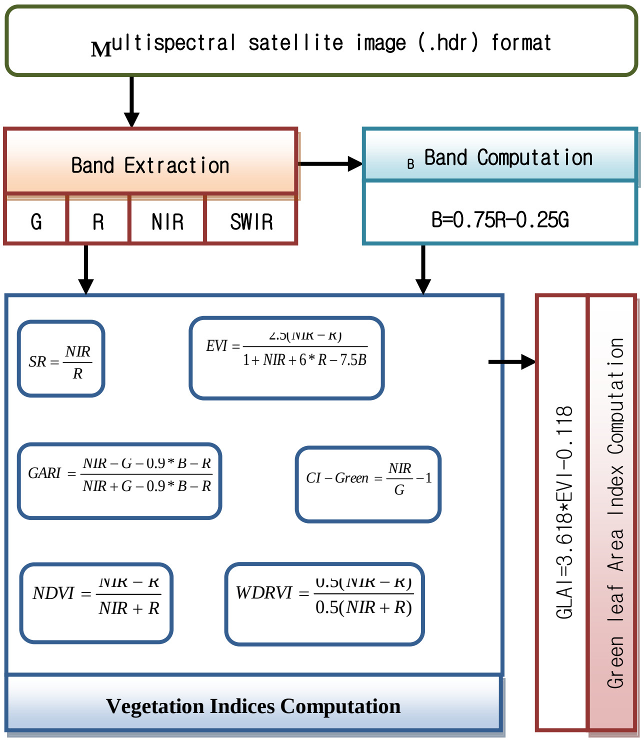


Figure. 2. Computation of vegetation indices and leaf area index

3.3 Crop image segmentation through FCM clustering

To achieve the task of segmentation, the indices matrix is converted to data matrix where the number of rows is equal to number pixels and number columns are equal to five which is accumulation of four neighbour pixels and the current one. Here, segmentation is carried out then using clustering by inputting the data matrix. Clustering is one of the methods for image segmentation after the introduction of k-means clustering algorithm (J. McQueen, 1967,), which is well-known algorithm for clustering due to its simplicity. Due to the success of k-mean clustering for image segmentation, variants of k-means clustering algorithms are developed by different researchers. One of the most accepted methods of clustering after the introduction of k-means clustering is FCM (J.C. Bezdek, 1981.), which is a well-liked algorithm integrating the fuzzy concept in finding the cluster centroids. The objective of clustering problem can be represented in another way utilizing the fuzzy membership function along with the distance variable. Let the objective function of FCM (J.C. Bezdek, 1981.)

$$OB_{FCM} = \sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}^{\ b} \left\| x_i - m_j \right\|^2 \qquad (10)$$

The detailed steps of the FCM algorithm is explained in the following sub steps:

1. Initialize the membership matrix randomly.

2. Compute the centroids based on the following equations

$$m_j = \frac{\sum_{i=1}^{n} u_{ij}{}^{b} . x_i}{\sum_{i=1}^{n} u_{ij}{}^{b}} \tag{11}$$

3. Update the membership matrix

$$u_{ij}{}^{b} = \frac{\left(\left\| x_i - m_j \right\|^{\frac{-1}{b-1}} \right)}{\sum_{j=1}^{m} \left(\left\| x_i - m_j \right\|^{\frac{-1}{b-1}} \right)} \tag{12}$$

4. Go to step 2 until maximum iteration is reached

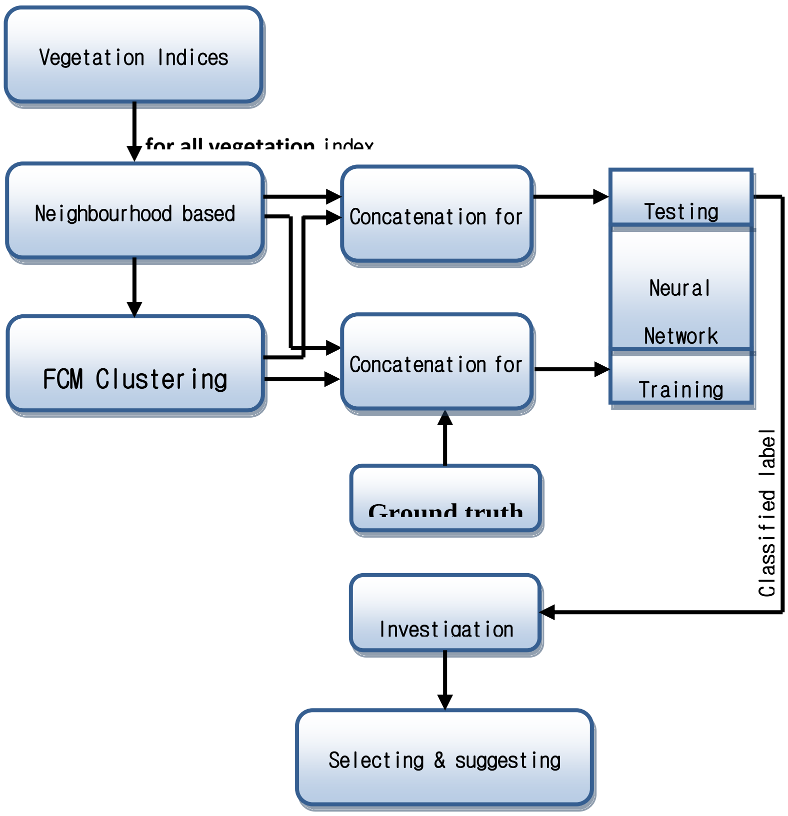


Figure. 3. Steps of Crop image classification

3.4 Crop image classification through feed forward neural network

This section describes the cotton crop classification through the feed forward neural network (FFNN) which is trained using LM algorithm. To train the neural network, the data matrix given for the clustering will be concatenated with the segment label generated clustering. The reformulated input is given to neural network for training along with the ground truth information which is used to learn the neural network whether the input pixels are cotton crop or not. The FFNN used in the proposed architecture has six input layer and one output layer. The input of the neural network is pixel value and its four neighborhoods along with segmented label of the clustering and the output layer provides the information whether its cotton crop or not. The proposed neural network architecture for the classification method is given in figure 4.

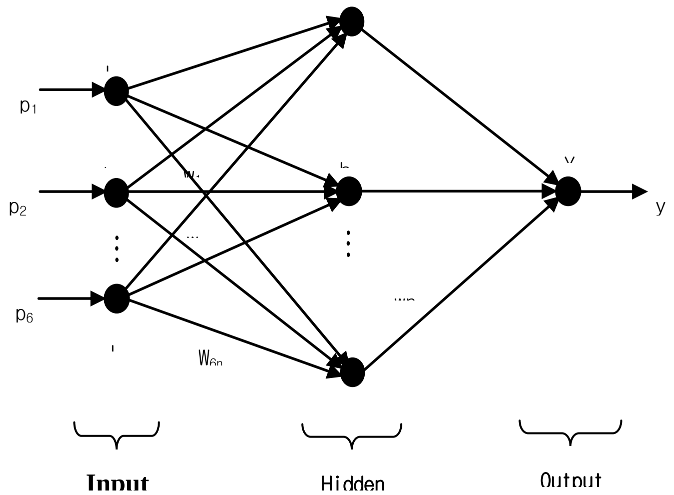


Figure. 4. Pixel-based classification through Feed forward neural network

The proposed neural network should learn the input data through the weight optimization algorithms. Here, we have used LM algorithm for weight learning procedure. Initially, the weights are randomly taken and every iteration, the weights are changed based on the following equation. In LM algorithm, the new weights are updated using the following equation given as:

$$w_{t+1} = w_t + \Delta w \tag{13}$$

Where, Δw is computed as follows,

$$\Delta w = [(J(v)) + \mu I]^{-1} J^T(v) e(v) \tag{14}$$

The Jacobean matrix $J(v)$ is defined by:

$$J(v) = \begin{bmatrix} \frac{\partial e_1(v)}{\partial v_1} & \frac{\partial e_1(v)}{\partial v_2} & \cdots & \frac{\partial e_1(v)}{\partial v_n} \\ \frac{\partial e_2(v)}{\partial v_1} & \frac{\partial e_2(v)}{\partial v_2} & \cdots & \frac{\partial e_2(v)}{\partial v_n} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{N_C}(v)}{\partial v_1} & \frac{\partial e_N(v)}{\partial v_2} & \cdots & \frac{\partial e_N(v)}{\partial v_n} \end{bmatrix} \tag{15}$$

$e(v)$ Is the error computation in the previous iteration, μ are the mean values, I and is the identity matrix.

In testing phase, the optimal weights learned by LM algorithm is kept and the trained neural network provides the output value for any inputs by multiplying an adding the weights value. Then, a threshold is fixed to convert the output score values into Boolean value which provides whether the input is cotton crop pixels or not.

4. RESULTS AND DISCUSSION

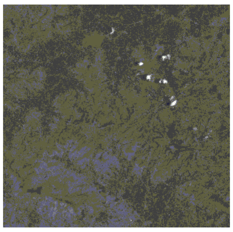
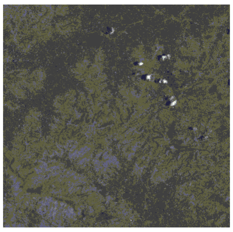
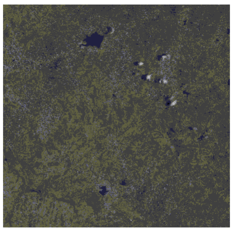
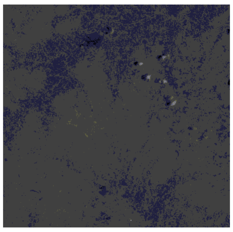
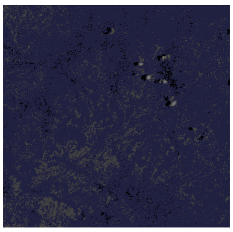
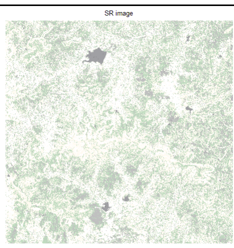
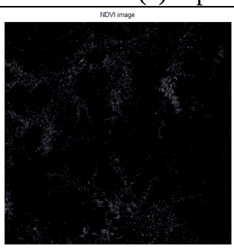
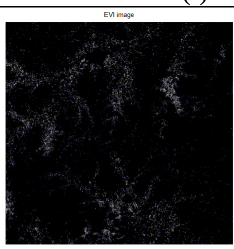
This section presents experimental results and the detailed analysis of the proposed system with different vegetation indices. Section 4.1 discusses the study area and section 4.2 discusses the experimental outcome in visualized format and the investigation report was given in section 4.3.

4.1 Study Area and Dataset description

The study area utilized for this research was Aurangabad (19° 53′ N, 75° 23′ E) region, in Maharashtra province of India. Here, satellite image with temporal variations through temporal LISS-III images were selected for cotton crop identification from Indian Remote Sensing Satellite (IRS-P6). The image taken from the specified area consists of five images which are taken from May 2010 to February 2011. In that time, three important scenarios were considered like pre-sowing (one image), flower to open ball (three images) and harvesting (one image) stage respectively. These three set of scenarios with five different satellite images are taken for the experimental purpose of this study.

4.2. Experimental results

The sample results of 'May2010" are given in figure 5. The four bands of input satellite image is given from figure 5.1 to 5.d and seven indices images is given from figure 5.f to 5.l. Then, segmented images are given in figure 5.m and the neural network training plot is given in figure 5.n. The final output generated by the neural network is given figure 5.o.

	
(a) Input image-G band	(b) Input image-R band
	
(c) Input image-NIR band	(d) Input image-SWIR band
	
(e) Input image-B band	(f) SR image
	
(g) NDVI image	(h) EVI image

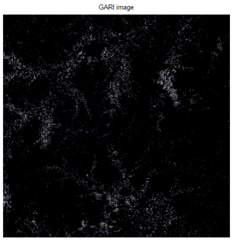
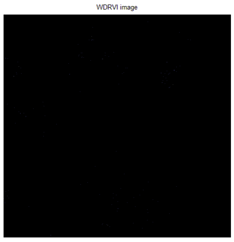
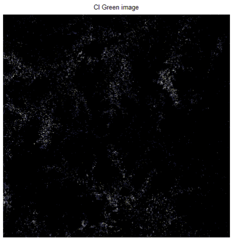
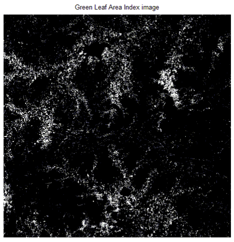
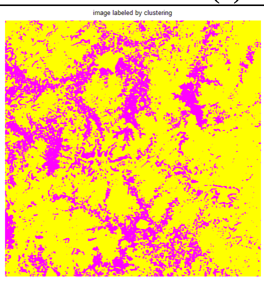
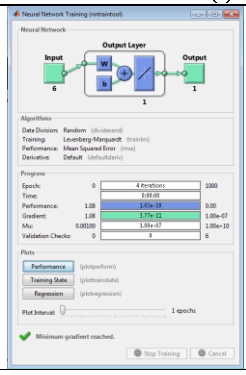
	
(i) GARI image	(j) WDRVI image
	
(k) CI_{green}	(l) GLAI image
	
(m) FCM segmented output in SR image	(n) Neural network-Training plot

Figure. 5. Sample results of image, “May2010”

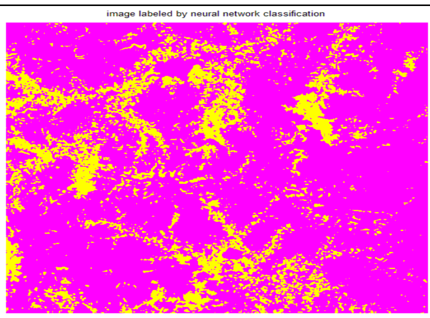
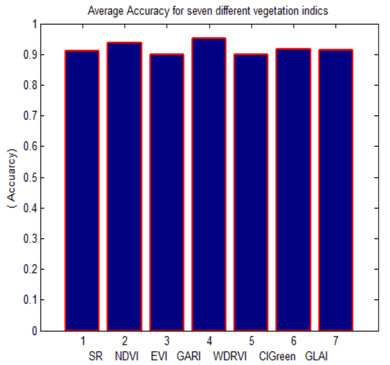


Figure.6.Final output by neural network in SR image

4.3 Investigation of different vegetation indices

To investigate the performance of the different vegetation indices, five different input images are taken and the classification system read the input individually to do the classification through different indices. For each index, the accuracy was computed and plotted in figure 6. The accuracy is the ratio of correctly classified pixels to the total number of pixels in the image. For the image May2010 and Nov2010, the maximum accuracy was reached by the GARI measure which outperformed better as compared with other measures. Similarly, the maximum accuracy was reached in Dec2010 image was by EVI measure and NDVI measure. For the Jan2011, NDVI measure and GLAI measure proved better classification as compared with other measures taken for investigation. For the images of Mar2011, GARI measure proved better crop region by reaching the maximum accuracy. Figure 7 plots the average accuracy of the five different images taken for the investigation. In the average performance, GARI measure outperformed with all other indices by reaching the accuracy value of 95.21%. Then, NDVI measure achieved the second rank with the accuracy of 93.57% and subsequently the $CI_{green,}$ GLAI and SR measure obtained the accuracy of 91.57%, 91.44% and 90.97%



Vegetation indices	Accuracy
SR	0.9097
NDVI	0.9357
EVI	0.8978
GARI	**0.9521**
WDRVI	0.8993
CI_{green}	0.9157
GLAI	0.9144

Figure. 7. Average Accuracy of five images

5. CONCLUSION

We have presented a methodology for cotton crop identification using fuzzy clustering combined with neural network algorithm which makes use of Levenberg-Marquardt algorithm for training. The input multispectral image was given to the proposed method to compute the six different vegetation indices along with the GLAI. Then, for every index, the proposed method was performed by applying FCM clustering for segmentation and neural network for classification. Finally, the accuracy of detecting the cotton crop region was computed for all measures. Here, the experimentation was done with five LISS-III satellite images taken from Maharashtra province of India. The main intuition of suggesting the better vegetation indices for cotton crop identification was performed with these five time-series images of pre-sowing (one image), flower to open ball (three images) and harvesting (one image) stage respectively. From the experimental outcome, the suggestion is to keep on with GARI measure which outperformed with all other indices by reaching the average accuracy value of 95.21%. In future, the research can be extended with, predicting the change of cultivation regions with time information through time series prediction model .

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