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Comparision of Clustering Algorithms usingNeural Network Classifier for Satellite Image Classification

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Abstract-
This paper presents a hybrid clustering algorithm and feed-forward neural network classifier for land-cover mapping of trees, shade, building and road. It starts with the single step preprocessing procedure to make the image suitable for segmentation. The pre-processed image is segmented using the hybrid genetic-Artificial Bee Colony(ABC) algorithm that is developed by hybridizing the ABC and FCM to obtain the effective segmentation in satellite image and classified using neural network . The performance of the proposed hybrid algorithm is compared with the algorithms like, k-means, Fuzzy C means(FCM), Moving K-means, Artificial Bee Colony(ABC) algorithm, ABC-GA algorithm, Moving KFCM and KFCM algorithm.

Keywords: *ABC-FCM, Segmentation Algorithm, Neural Network, Feature Extraction, Satellite Image Classification*

I. Introduction

Image segmentation is a critical step of image analysis. The task of image segmentation can be stated as the clustering of a digital image into multiple meaningful non-overlapping regions with homogenous characteristics according to some discontinuity or similarity features like intensity, color or texture [1,2].

Depending on the way to deal with uncertainty about the available data, the clustering process can be categorized as Hard clustering or Fuzzy clustering. A hard clustering algorithm partitions the dataset into clusters such that one object belongs to only one cluster. This process is inappropriate for real world dataset in which there are no clear boundaries between the clusters. Since the inception of the fuzzy set theory thanks to Zadeh' work [3], researchers incorporate the concept of fuzzy within clustering techniques to handle the data uncertainty problem. The goal of unsupervised fuzzy clustering is to assign each data point to all different clusters with some degrees of membership.

The iterative unsupervised Fuzzy C-Means (FCM) algorithm is the most widely used clustering algorithm for image segmentation [4]. Its success is mainly attributed to the introduction of fuzziness about the pixels'membership to clusters in a way that postpones decision making about hard pixels' membership to latter.

Satellite image categorization field is quiet a challenging job. Recently, researchers have used different types of classification methods for enhancement of efficiency. Satellite image classification, an upgraded biologically motivated theory was applied by Lavika Goel [5]. This paper related to a study of their hybrid intelligent classifier along with other current Soft Computing classifier like: 1) Ant Colony Approach, 2) Hybrid Particle Swarm Optimization-cAntMiner (PSO-ACO2), 3) Fuzzy sets, 4) Rough-Fuzzy Tie up; the Semantic Web Based Classifiers and the traditional probabilistic classifiers such as the Minimum Distance to Mean Classifier (MDMC) and the Maximum Likelihood Classifier (MLC).

A hybrid Biogeography Based Optimization(BBO) algorithm, which is an excellent land cover classifier for satellite image has been introduced by Navdeep Kaur Johal *et al.* [6]. Parminder Singh *et al.* have presented a FPAB/BFO based algorithm for the categorization of satellite image[7]. They intend to utilize the technique of Bacterial Foraging Optimization in order to categorize the satellite image.

M. Ganesh and V. Palanisamy have approached a method known as multiple-kernel fuzzy clustering (MKFCM) for satellite image segmentation[9]

This paper proposes a hybrid clustering algorithm and neural network classifier for satellite image classification.

In this work ABC algorithm and FCM are combined to improve the segmentation of images.

This paper is structured as follows: Second section delineates proposed technique, third section discusses analysis and the fourth section is conclusion.

II. Proposed Technique ABC-FCM and Neural Network

This section explains the proposed satellite image classification based on hybrid ABC-FCM algorithm and Feed-Forward Neural Network. The classification would be done based on building, road, shade and tree. The proposed technique is discussed in two phases which are training and testing phases.

2.1Training Phase

Input: Satellite images for training
Output: Trained neural network

1. *Start*
2. Get the satellite image for training
3. Preprocess the image
4. Separate the regions we need to classify from image
5. *For* each region
6. Extract the feature layers H, S, L, T, A, B, U and V
7. *For* each feature layer
8. Evaluate histogram
9. Extract the feature values
10. *End for*
11. *End for*
12. Three neural networks are taken to train the building, road and shade regions separately
13. *For* each neural network
14. Give corresponding feature values to train it
15. *End for*
16. The neural network would be trained
17. *Stop*

2.2 Testing Phase:

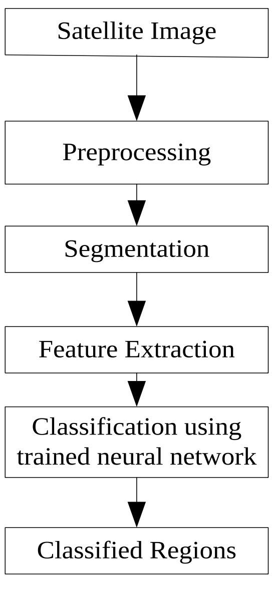

Fig.1 *Process of Testing Phase*

The Fig.1 explains as follows: the input satellite image is given for pre-processing using median filtering technique and the output of median filter is used for segmentation process is done. In segmentation process, initially the H, T and L layers are extracted from the pre-processed image and the layers are given separately to the ABC-FCM algorithm to cluster it. Thereafter, the clustered layers are merged one another and the feature extraction process is used on each merged clusters and then the extracted feature values of each merged clusters are applied to the trained neural networks to classify the building, road, shade and tree regions of the given input satellite image.

2.2.1 Segmentation

In segmentation process, the input pre-processed satellite image is converted to HSL(Hue,Saturation,Intensity),TSL(Tint,Saturation,Intensity),and LAB(lightness,color opponent dimensions) color spaces and the H, T and L layers are extracted from it. Thereafter, the ABC-FCM algorithm is applied on each layer (H, T and L) separately to cluster the pixels. Here, the FCM operator is incorporated in the ABC algorithm to segment the satellite image effectively. In ABC system, the artificial bees fly around in a multidimensional search space and some (employed and onlooker bees) choose food sources conditional on the experience of themselves and their nest mates, and amend their positions. Some (scouts) fly choose the food sources randomly without using experience. If the nectar amount (fitness) of a new source is higher than that of the previous one in their memory, they memorize the new position and forget the previous one. Thus, the ABC system combines the local search method and global search method to balance the exploration and exploitation process. The local search method is carried out by employed and onlooker bees and the global search method are carried out by onlookers and scouts. In ABC algorithm, the colony of artificial bees contains three groups of bees: employed bees, onlookers and scouts. A bee waiting on the dance area for making a decision to choose a food source is called onlooker and one going to the food source visited by it before is named employed bee. The other kind of bee is scout bee that carries out random search for discovering new sources. The position of a food source represents a possible solution to the optimization Problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. Here, the FCM operator is incorporated with the ABC algorithm to enhance the segmentation of the satellite image effectively. The advantage of FCM algorithm is that it allows a single pixel to belong to two or more clusters.

2.2.1.1ABC-FCM Algorithm

The segmentation process is done based on ABC-FCM algorithm. Consider the ABC-FCM algorithm is applied on H layer. The process is as follows: initially fixed numbers of initial solutions (food sources) are generated randomly by giving lower bound and upper bound. Each solution would contain the centroids based on the required number of clusters. The Fig.2 shows the sample solutions generated randomly.

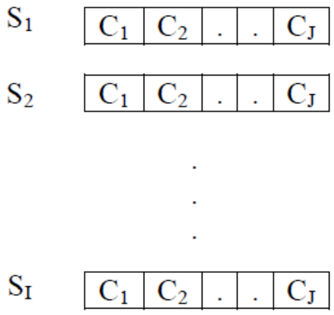

***Fig.2** Sample Solutions*

In this Fig.2, *S* denotes the solution (food source); *I* denotes the total number of solutions generated; *C* denotes the centroid in the solution; and J denotes the total number of centroids generated. After initial solutions are generated, the fitness is calculated for each solution. The calculation of fitness is as follows: initially the centroids in each solution are taken for clustering process and the clustering is done based on the minimum distance. The fitness is then calculated based on the equation given below:

$$fit_i = \sum_{j=1}^{J} \sum_{a=1}^{A} \left\| \left(x_a - C_j \right) \right\|^2$$

In the above equation fit_i denotes the fitness of ith solution, where i=1,2 ---J; and x_a denotes ath pixel x in jth cluster; and j=1,2 ---J ; A is the total number of pixels in jth cluster, where; and Cj denotes the centroid C of jth cluster.

Employed Bee Operation

The employed bee then makes modification on the solution in its memory based on the local visual information and then calculates the nectar amount (fitness) of the new solution. If the nectar amount of the new solution is better than the old one, the bee would memorize the new one and forgets the old one. Otherwise it would keep the position of the old one in its memory. The employed bee operation is performed on each solution. To produce a candidate food position from old one in memory, the ABC uses the following expression:

$$S_{ij}^{new} = S_{ij} + \phi_{ij}\left(S_{ij} - S_{kj}\right)$$

In the above equation, $k \in \{1,2,...., I\}$and $j \in \{1,2,...., J\}$are randomly chosen index. Though k is determined randomly, it is different from i. i.e. Sij denotes the jth centroid of i th solution S; and S_{kj} denotes the jth centroid of kth solution of S. The Φ_{ij} in the above equation is a random number between (-1,1) and it controls the production of neighbor food sources around S_{ij} and represents the comparison of two food positions visible to a bee. Using the above equation the jth centroid of ith solution S would get altered. We can alter two or more centroids based on the above equation and we would get a new solution. From the above formula the perturbation on the position S_{ij} decreases as the difference between the parameters S_{ij} and S_{kj} decreases. Therefore the step length is adaptively reduced as the search approaches to the optimum solution in the search space. After the employed bee operation is performed on each solution, the fitness is calculated for each newly formed solution. If the nectar amount of the newly formed solution is better than the old one, the employed bee would memorize the new one and forgets the old one. The employed bees then share the nectar (fitness) information with the onlooker bees on the dance area.

Onlooker Bee Operation

The onlooker bee then evaluates the nectar information taken from all employed bees and chooses a food source with a probability to its nectar amount. The probability value is calculated for each solution and it calculated by the following equation:

$$\Pr_i = \left(\frac{0.25}{\max(fit)} \right) \times fit_i + 0.1$$

In the above equation $\Pr_i$ is the probability of ith solution; max(fit) is the maximum fitness value among all the solutions; and fit_i is the fitness value of ith solution. After calculating the probability of ith solution, the onlooker bee would check whether $\Pr_i$>*rand* , where *rand* is a randomly generated number between zero and one. If it so, the onlooker bee would produce a new solution instead of this ith solution. The new solution is formed based on the operation performed by the employed bee i.e. based on S_{ij}^{new} calculation. Then it would calculate the fitness (nectar amount) for the newly generated solution and compare with the old one. If the fitness of the newly formed solution is better than the old one, it would memorize the new one and forgets the old one.

Scout Bee Operation

The food source of which the nectar is abandoned by the bees is replaced with a new food source by the scouts i.e. the solutions which are not altered by any one of operations (which are employed bee operation and onlooker bee operation) is replaced by a new solution using scout bees. Consider ith

solution is not altered using either of employed bee operation and onlooker bee operation, the scout bee operation is performed on the ith solution as defined below:

$$S_i^j = S_{\min}^j + rand(0,1)(S_{\max}^j - S_{\min}^j)$$

In the above equation S_{ji} is the jth centroid of ith solution; $S_{\min}^j$ is the minimum jth centroid value among all the solutions; rand(0,1) is the random value between 0 and 1; and $S_{\max}^j$ is the maximum jth centroid value among all the solutions. The scout bee operation is performed only if there has any abandoned solution. ABC operation is repeated until the iteration number set and a solution that has best fitness in the final iteration is taken for the FCM operation.

FCM Operation

The best solution obtained from the ABC process is taken for the FCM operation. The FCM is a clustering technique that allows a single pixel to belong to two or more clusters. The degree of membership matrix is formed based on the solution obtained from the ABC process. The Fig.8 shows the degree of membership matrix.

	C_1	C_2	.	.	C_J
x_1	u_{11}	u_{12}	.	.	u_{1J}
x_2	u_{21}	u_{22}	.	.	u_{2J}
x_3	u_{31}	u_{32}	.	.	u_{3J}
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
x_L	u_{L1}	u_{L2}	.	.	u_{LJ}

Fig.3 *Degree of membership matrix*

In the Fig.3, $\{x_1,x_2\ldots..x_l\}$ represents the pixels in the particular layer taken for clustering; and $\{C_1,C_2$— $C_j\}$ represents the centroids in the best solution obtained from the ABC process; and u_{ij} is the degree of membership of Xj in jth cluster, where l={1,2….L},j={1,2…..J}. The u_{ij} is the distance between Lth pixel and jth centroid. The new centroids are then formed based on the equation given below:

$$C_j = \frac{\sum_{l=1}^{L} u_{lj}^m * x_l}{\sum_{l=1}^{L} u_{lj}^m}$$

In the above equation C_j is jth centroid; x_l is the lth pixel; and m is the fuzzyness coefficient which has the value set as two. Thereafter, new degree of membership values is calculated based on the newly formed centroids. The new membership values are calculated as follows:

$$u_{lj} = \frac{1}{\sum_{k=1}^{J}\left(\frac{\|x_l - C_j\|}{\|x_l - C_k\|}\right)^{2/m-1}}$$

The fuzzy operation is repeated until the iteration numbers set and the centroids obtained in the final iteration are chosen as the centroids to cluster the pixels. The clustering is then done by grouping the least distance pixels to the chosen centroids. Similarly the ABC-FCM algorithm is applied on T and L layers separately to cluster the pixels in it.

2.2.1.2Merging Clustered Layers

The clusters formed from the H, T and L layers are then merged with one another. For instance consider three clusters are formed from each layer. The clusters formed from H layer are denoted as CH1, CH2 and CH3; and the clusters formed from T layer are denoted as CT1, CT2 and CT3; and the clusters formed from L layer are denoted as CL1, CL2 and CL3. Based on the clusters obtained from each layer, the merging process is done as follows: the first merged group contains CH1, CT1 and CL1; and the next would contain CH1, CT1, CL2; and the next would contain CH1, CT1, CL3; and so on. Each merged group is then given for the feature extraction process.

2.3Classification

The feature extraction process is done in the same way as in the training phase on each merged group i.e. the H, S, L, T, A, B, U and V layers are extracted from each merged group to calculate the feature values. The feature values from the feature extraction process of each merged group are then given to the trained neural network to classify the regions. In our training process we use three neural networks to classify the regions. The process of classification is as follows: the feature value of the first merged group is given to the first neural network to check whether it has building region or not, because the first neural network is trained to identify building region. If not, the feature value is then given to the second neural network to check whether it has road region, because the second neural network is trained for road region. If not, the feature value is given to the third neural network to check whether it has shade region, because the third neural network is trained for shade region. If not, the system would take it as tree region. Similarly, the feature value obtained for each merged group is given to the trained neural network to classify the regions.

III. Result and Discussion

This section delineates the results obtained for our proposed technique compared with the existing segmentation techniques. The performances are compared in terms of external metrics and internal metrics. The external metric is accuracy performs the evaluations based on ground truth. The internal metrics are Davies–Bouldin (DB) index, Xie-Beni (XB) validity index and Mean Square Error (MSE) performs the evaluations without ground truth.

3.1. Evaluation Metrics

The metrics used for evaluation are sensitivity, specificity, accuracy, DB index, XB index and MSE. The calculations of metrics are as follows:

$$accuracy = \frac{(number\ of\ true\ positives + number\ of\ true\ negatives)}{(number\ of\ true\ positives + false\ negatives + true\ negatives + false\ positives)}$$

DB Index

The Davies Bouldin (DB) Index is a metric exploited to evaluate the clustering algorithm. The DB-Index is an internal evaluation scheme that validates how well the cluster is done based on the quantities and features inherent to the dataset. The DB-Index calculation is as follows:

$$DBI = \frac{1}{N}\sum_{n=1}^{N} D_{n,n+1}$$

Where, $D_{n,n+1} = \frac{d_n + d_{n+1}}{M}$

$$d_n = \frac{1}{T}\sum_{b=1}^{T} \left|X_b - C_n\right|^2$$

$$M = \sum_{n=1}^{N-1}\sum_{f=n+1}^{N}\sqrt{\left(C_n - C_f\right)^2}$$

In the above equations DBI denotes the Davies Bouldin (DB) Index, N denotes total number of clusters, $d_{n,n+1}$ denotes clustering scheme measurement between each cluster, d_n denotes the value of distance between each data in the n^{th} cluster and centroid of that cluster, d_{n+1} denotes the value of distance between each data in the next cluster and the centroid of n^{th} cluster, M denotes sum of the Euclidean distance between each centroid, T is the total number of data in the cluster, X is the data in the n^{th} cluster and C_n is the centroid of n^{th} cluster.

XB Index

The XB-Index is the ratio of within cluster compactness to the minimum separation of clusters. It is defined as follows:

$$XBI = \frac{E}{g \times h}$$

In the above equation E denotes sum of Euclidean distance between the centroids and its respective data; and g is the total number of data; and h is the minimum distance between the centroids. It is shown by an equation below:

$$h = \min\left\{dis\left(C_n, C_f\right)\right\}$$

In the above equation n varies from 1 to N-1, where N is the number of clusters; and f varies from n+1 to N. The above equation compares the distance between each centroid and it would choose the minimum distance value.

Mean Square Error

The Mean Square Error (MSE) for a clustering is done by summing the least distance value between the centroid and data of each cluster. The best cluster would have the nearest data of the centroid in it. It is defined as follows:

$$MSE = \sum_{n=1}^{N} \min\ dis\left(X_b, C_n\right) \qquad where,\ b = 1,2,....,T$$

In the above equation N is the total number of clusters, X_b is the b^{th} data in n^{th} cluster, C_n is the centroid of n^{th} cluster and T is the total number of data in the n^{th} cluster.

3.2. Performance Comparison

The performance of proposed technique is compared with the existing segmentation algorithms such as k-means, FCM, Moving K-means, ABC algorithm, ABC-GA algorithm, and KFCM algorithm in terms of external metrics and internal metrics using different satellite image. The Fig.4(a) shows the satellite images taken for experimentation and the Fig.4(b) shows the classified regions for image.

Fig.4(a) *Satellite Image*

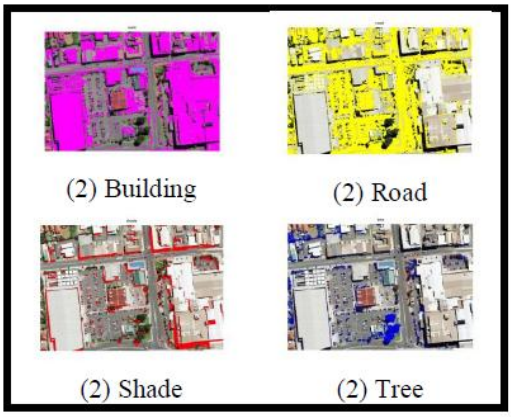

Fig.4(b) *Classified regions*

3.2.1. Performance Based on External Metrics

The Fig.6 shows the accuracy obtained for technique compared to the existing techniques using image taken for experimentation.

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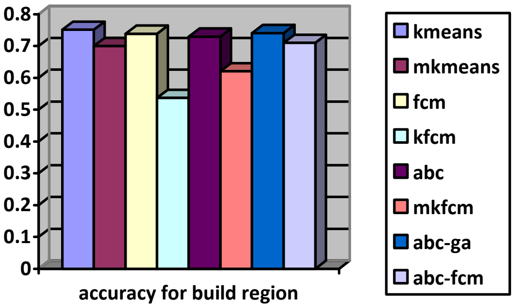

Fig.5(a)

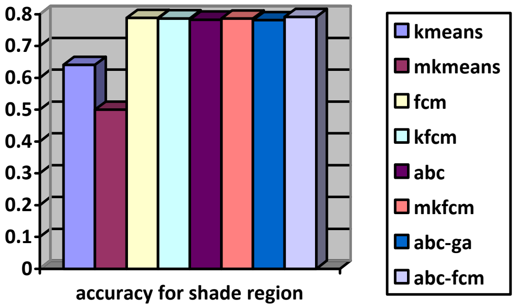

Fig.5(b)

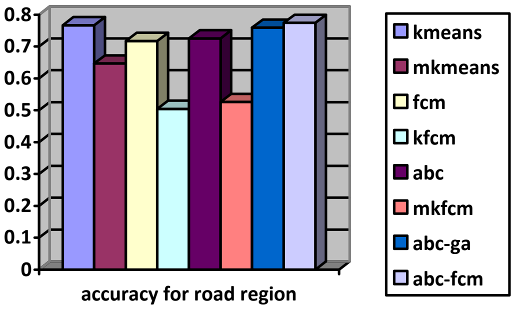

Fig.5(c)

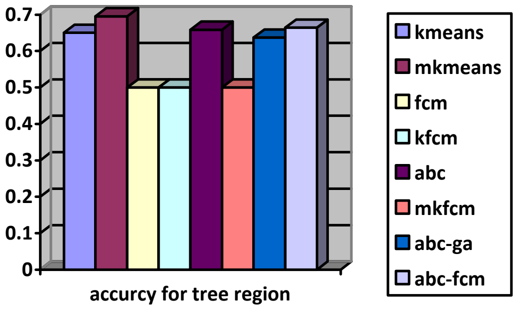

Fig.5(d

In Fig.5(a) the accuracy obtained for the proposed segmentation algorithm ABC-FCM is compared with the existing techniques using input image taken for experimentation. As shown in proposed technique performed better than all the existing algorithms taken for comparison except Moving Kmeans algorithm. In shade region classification, the proposed technique and the MKFCM performed almost similar and better compared to all the other techniques taken for comparison. In road region classification, proposed technique performed better than the other techniques taken for comparison. The result indicates that proposed ABC-FCM is performed better than the existing algorithms KFCM, ABC and MKFCM for building region classification.

3.2.2. Performance Based on Internal Metrics

This section shows the performance comparisons by means of DB-index, XB-index and MSE for all the three satellite images taken for experimentation. The better performances of these indices are judged based on less value. The Fig.6 shows the DB-index, XB-index and MSE performances of proposed technique compared to the existing techniques.

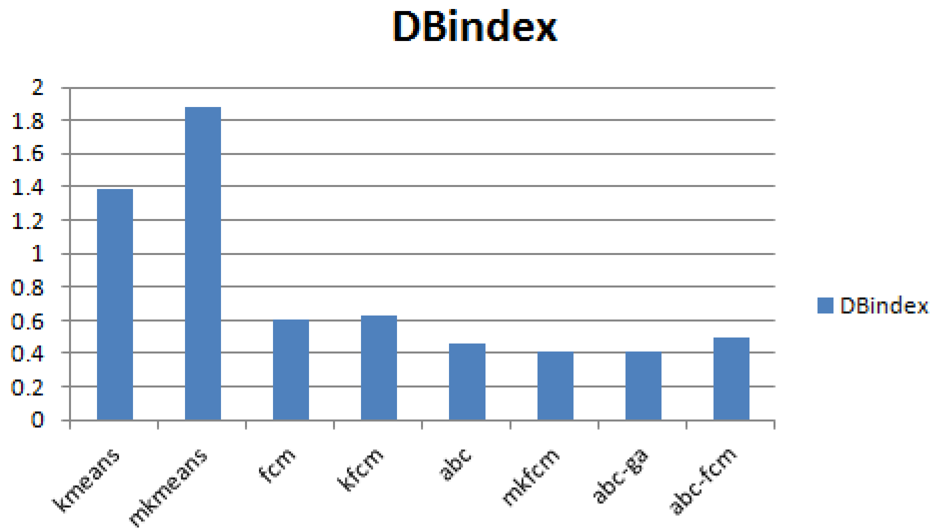

Fig.6(a) *DB-Index*

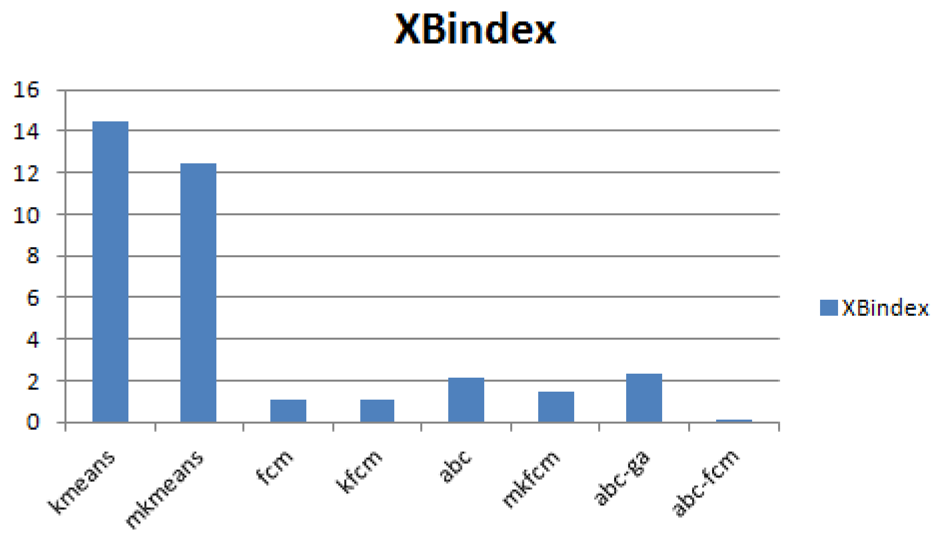

Fig.6(b) *XB-Index*

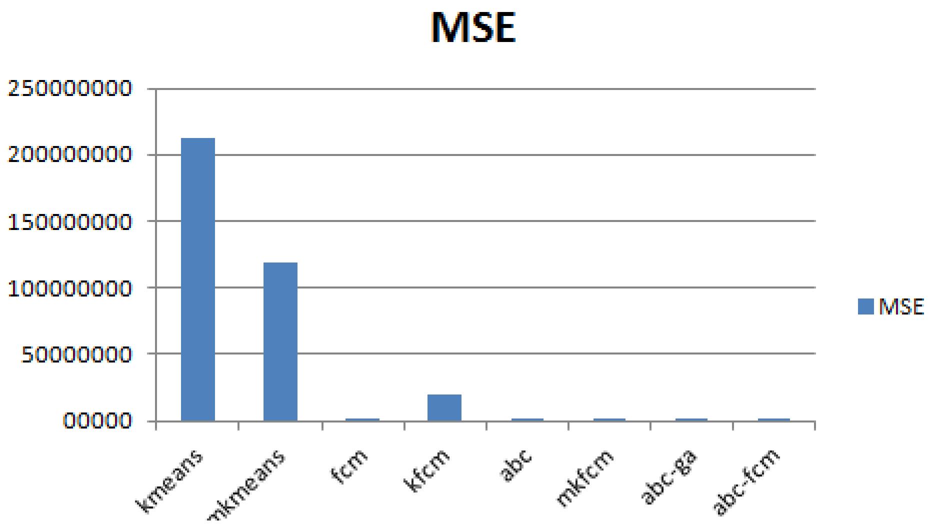

Fig.6(c) *MSE*

The Fig6(a) shows the DB-index comparison using second image taken for our experimentation and the Fig.6(b) shows the XB-index comparison using second image and the Fig.6(c) shows the MSE comparison for a given input image. Here in DB-index comparison, the performance of the proposed technique is better compared to Kmeans, MKmeans, FCM and KFCM algorithms. In XB-index comparison, the proposed technique is better compared to all the other techniques taken for comparison. In MSE comparison, the performance of the proposed technique, ABC, MKFCM and ABC-GA are almost similar and better compared to Kmeans, MKmeans, FCM and KFCM algorithms.

IV. Conclusion

In this paper, a new optimization algorithms for image segmentation satellite images using feed-forward neural network classifier is proposed. The steps involved in the proposed technique are, i) Pre-processing, ii) segmentation using genetic-ABC algorithm, and iii) classification using feed-forward neural network classifier.

Initially pre-processing is performed to make the image suitable for segmentation. In segmentation, the preprocessed image is segmented using ABC-FCM algorithm that is developed by hybridizing the ABC and FCM algorithm to obtain the effective segmentation in satellite images. Then, feature is extracted and the classification of satellite image into four different labels (tree, shade, road and building using network classifier. Finally, classification accuracy of the proposed algorithm in satellite image classification is calculated and the performance is compared with various clustering algorithms.

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