Object based Classification for SAR Images with Bacterial Forging Integration

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Abstract— Automatic image classification is the task of classifying images into semantic categories with or without supervised training. As the traditional techniques for the automatic Image Classification have their certain shortcomings like high resolution images needed for better information retrieval, and the accuracy limitations are also there. Also the recent Soft Computing approaches for Image Classification are not able to provide good results in case of ambiguity. So for achieving the better accuracy even with the low resolution satellite images and better land cover mapping we are using the Swarm Intelligence for Bacterial forging Image Classification. Our main objective is to use the Swarm intelligence for the image classification for Land Cover Mapping. Here we are using the algorithm of Swarm intelligence i.e. Bacterial forging for the Satellite Image Classification, so that we can retrieve the more accurate information about any Land Area even with the low resolution satellite images. This approach is used because it provides the greater speed and accuracy in its computation.

Keywords— *Synthetic Aperture Radar (SAR) Image, Remote Sensing, Satellite Image; Image Classification Techniques; Bacterial Foraging Optimization Algorithm (BFOA).*

I. INTRODUCTION

SAR images are the satellite captured high resolution images which are having higher significance in various real time applications including water region identification, forest identification etc. These images are interpreted to analyze the associated feature to identify the category of image. The region analysis can be done based on texture analysis or the statistical observation. The work model is here presented to classify the images from the pool based on content analysis. The work will be able to identify water, building, mountain etc. strengthen images accurately and effectively. To create a SAR image, successive pulses of radio waves are transmitted to “illuminate” a target scene, and the echo of each pulse is received and recorded. The pulses are transmitted and the echoes received using a single beam-forming antenna, with wavelengths of a meter down to several millimeters. As the SAR device on board the aircraft or spacecraft moves, the antenna location relative to the target changes with time. Signal processing of the successive recorded radar echoes allows the combining of the recordings from these multiple antenna positions – this process forms the 'synthetic antenna aperture', and allows the creation of higher resolution images than would otherwise be possible with a given physical antenna. SAR images have wide applications in remote sensing and mapping of the surfaces of both the Earth and other planets. SAR can also be implemented as inverse SAR by observing a moving target over a substantial time with a stationary antenna. Applications of SAR images are:

- Glacier monitoring
- Sea ice mapping
- Wind movement on ocean surface
- Mapping of Antarctic
- Volcano inflation and deflation
- Urban signatures
- Land cover mapping/monitoring
- Geomorphology and ocean surface during hurricanes

SAR Image processing steps shown in Figure 1.

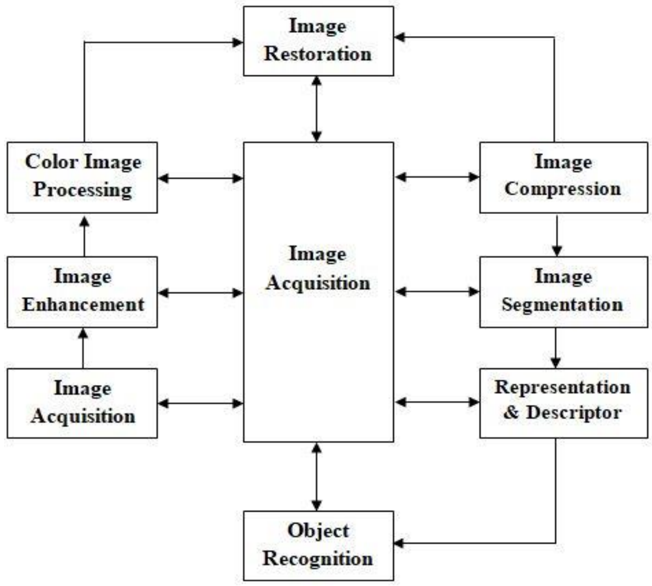


Figure1: SAR Image Processing.

A. *Image Acquisition*

This is the first step or process of the fundamental steps of digital image processing. Image acquisition could be as simple as being given an image that is already in digital form. Generally, the image acquisition stage involves preprocessing, such as scaling etc.

B. *Image Enhancement*

Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image. Such as, changing brightness & contrast etc.

C. Image Restoration

Image restoration is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation.

D. Compression

Compression deals with techniques for reducing the storage required to save an image or the bandwidth to transmit it. Particularly in the uses of internet it is very much necessary to compress data.

E. Segmentation

Segmentation procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually.

F. Representation and Description

Representation and description almost always follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region or all the points in the region itself. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. Description deals with extracting attributes that result in some quantitative information of interest or are basic for differentiating one class of objects from another.

G. Object Recognition

Recognition is the process that assigns a label, such as, “vehicle” to an object based on its descriptors.

H. Knowledge Base

Knowledge may be as simple as detailing regions of an image where the information of interest is known to be located, thus limiting the search that has to be conducted in seeking that information. The knowledge base also can be quite complex, such as an interrelated list of all major possible defects in a materials inspection problem or an image database containing high-resolution satellite images of a region in connection with change-detection applications.

II. RELATED WORK

Both visual interpretation and automatic analysis of data from imaging radars are complicated by a fading effect called speckle, which manifests itself as a strong granularity in detected images (amplitude or intensity). For example, simple classification methods based on thresholding of gray levels are generally inefficient when applied to speckled images, due to the high degree of overlap between the distributions of the different classes. Speckle is caused by the constructive and destructive interference between waves returned from elementary scatterers within each resolution cell. It is generally modeled as a multiplicative random noise.

Compared with optical image, SAR image has more legible outline, better contrast and more plentiful texture information. The objects of different shape and physical feature take on different texture character, which is a critical technique of identifying objects by radar. At present, there are many approaches to image classification, but there is not an approach to suit all kinds of images. During the past years, different methods were employed for classification of synthetic aperture radar (SAR) data, based on the Maximum Likelihood (ML), artificial Neural Networks (ANN) fuzzy methods or other approaches. The NN classifier depends only on the training data and the discrimination power of the features. Fukuda and Hirosawa applied wavelet-based texture feature sets for classification of multi frequency polarimetric SAR images. The Classification accuracy depends on quality of features and the employed classification algorithm. For a high resolution SAR image classification, there is a strong need for statistical models of scattering to take into account multiplicative noise and high dynamics. For instance, the classification process needs to be based on the use of statistics. Clutter in SAR images becomes non-Gaussian when the resolution is high or when the area is man-made. Many models have been proposed to fit with non-Gaussian.

Scattering statistics (Weibull, Log normal, Nakagami Rice, etc.), but none of them is flexible enough to model all kinds of surfaces in our context. For SAR image classification problem many fuzzy models have been proposed, Fuzzy c-means clustering (FCM) algorithm is widely applied in various areas such as image processing and pattern recognition. Co-occurrence matrix and entropy calculations are used to extract transition region for an image. This transition region approach is used to classify the SAR images. However most of the work remains restricted to maximum 6 training sites

Synthetic Aperture Radar (SAR) image classification is becoming more and more increasingly important in military or scientific research. Region specification is a crucial step towards automatic classification of SAR images. Under some severe conditions of improper illumination and unexpected disturbances, the blurring images make it more difficult for target recognition, which results in the necessity of classification [1]. There is two basic approaches has been found in image classification is pixel based classification and object based classification. Object based image classification is deriving information from a set of similar pixels called image objects. The aim of the pixel based image classification is to assign each pixel of the image to a class with regard to a feature space. These features can be the basic image properties as intensity or amplitude [2].

It is important to classify the SAR images to know various areas around it. For example the SAR images are covered with various regions includes vegetation, land, building, Lake Etc. Identifying these regions in terms of classification will helps in various kinds of research work. Table 1 demonstrates that related work with image classification for Synthetic Aperture Radar (SAR images).

Table 1: Related Work with SAR Images.

S/No.	*Authors*	*Proposed Approaches*
[1]	**Yiqing Guo et. al. (2018)**	SVM-based Sequential Classifier Training (SCT-SVM) approach is proposed for multi temporal remote sensing image classification. The approach leverages the classifiers of previous images to reduce the required number of training samples for the classifier training of a new image.
[2]	**Dr. O. P. Malik et. al. (2017)**	A modified algorithm based on the Artificial Neural Network was designed for SAR images classification. The new algorithm is successfully applied for classification of SAR images. The experimental results consistently show that the proposed algorithm has high classification precision. When compared with other two classifiers, K-means, and FCM, the average performance of ANN is better than them.
[3]	**Charu Malik et. al. (2016)**	An exploration to the SAR image characterization and classification is provided. The paper has identified some of the application areas of SAR image processing. The paper also provided the description of some of common classification methods. These methods are defined based on distance level, probabilistic and decision criteria specification. Decision Tree, KNN, Bayesian Network and LDA methods are defined with relative procedure and constraints in this paper.
[4]	**Jie Geng(2015)**	It provided a work on SAR image classification using auto encoder. The feature representation based evaluation is applied to identify the difficulty region and provide the feature based modeling to overcome the associated problem. The deep network is composed of eight layers: a convolution layer to extract texture features, a scale transformation layer to aggregate neighbor information, four layers based on sparse auto encoders to optimize features and classify, and last two layers for post processing
[5]	**Guan Dong (2015)**	Used the local pattern descriptor as the SAR image classifier. The method of image quantization is based on recent local binary pattern. For an SAR image patch in a moving window, after quantization, different patterns can be obtained, which represent the local structures that exist in SAR image.
[6]	**Jilan Feng(2014)**	It presented a two stage approach for texture and amplitude feature based SAR image classification. The proposed approach is based on superpixels obtained with some over-segmentation methods, and consists of two stages. In the first stage, the SAR image is classified with amplitude and texture feature used separately. Author defines the CRF based on region adjacent graph (RAG) of superpixels.
[7]	**Shuiping Gou (2014)**	Used the eigen feature approach for SAR image classification. The approach consists of two parts. Initially, the statistical distributions of eigen value for homogeneous areas are analyzed by taking eigen values as the features of polarimetric information. The Bayesian classification method is applied to verify the feasibility of distinguishing different homogeneous areas
[8]	**Debabrata Samanta (2012)**	It presented a novel approach for SAR image classification using clustering and color space analysis. Author considers the problem of SAR image Classification by Histogram thresholding technique. Then Author proposed Color space clustering and Watershed Classification for merging different region to get the classified SAR images
[9]	**Narcisse Talla Tankam (2011)**	It considered the structural and statistical features for SAR image classification. Author defined the suitable size of the image window used in the proposed approach of supervised image classification. This approach is based on a new way of characterizing different classes identified on the image. The first step consists in determining relevant area of interest. The second step consists in characterizing each area identified, by a matrix. The last step consists in automating the process for image classification
[10]	**Dengxin Dai (2011)**	It used the local pattern based histogram for SAR image classification. The method describes the size distributions of bright, dark, and homogenous patterns appearing in a moving window at various contrasts; these patterns are the elementary properties of SAR image texture.

III. Image Processing in SAR

The raw data received from the imaging sensors on the satellite platforms or aircrafts contains flaws and deficiencies. To overcome these flaws and deficiencies in order to get the originality of the data, it needs to undergo several steps of processing. This will vary from image to image depending on the type of image format, initial condition of the image and the information of interest and the composition of the image scenes. . Digital Image Processing undergoes three general steps:

- Pre-processing
- Display and enhancement
- Information extraction

A. Pre-Processing

It consists of those operations that prepare data for subsequent analysis that attempts to correct or compensate for systematic errors. The digital imageries are subjected to several corrections such as geometric, radiometric and atmospheric, though all these corrections might not be necessarily be applied in all cases. These errors are systematic and can be removed before they reach the user. The investigator should decide which pre-processing techniques are relevant on the basis of the nature of the information to be extracted from remotely sensed data. After pre-processing is complete, the analyst may use feature extraction to reduce the dimensionality of the data. Thus feature extraction is the process of isolating the most useful components of the data for further study while discarding the less useful aspects (errors, noise etc).

B. Image Enhancement

Image enhancement operations are carried out to improve the interpretability of the image by increasing apparent contrast among various features in the scene. As an image enhancement technique often drastically alters the original numeric data, it is normally used only for visual (manual) interpretation and not for further numeric analysis. Common enhancements includes transect extraction, contrast adjustments, spatial filtering, Fourier transformations, etc.

C. Information Extraction

Information extraction is the last step toward the final output of the image analysis. After pre-processing and image enhancement the remotely sensed data is subjected to quantitative analysis to assign individual pixels to specific classes. Classification of the image is based on the known and unknown identity to classify the remainder of the image consisting of those pixels of unknown identity. After classification is complete, it is necessary to evaluate its accuracy by comparing the categories on the classified images with the areas of known identity on the ground. The final result of the analysis consists of maps (or images), data and a report. These three components of the result provide the user with full information concerning the source data, the method of analysis and the outcome and its reliability.

IV. Image Classification

The Image classification is formally defined as the process whereby a received pattern/signal is assigned to one of a prescribed number of classes. The overall objective of image classification procedures is to automatically categorize all pixels in an image into land cover classes or themes. Normally multi-spectral data are used to perform the classification and used to perform the classification and indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorize spectral pattern refers to the set of radiance measurements obtained in the various wavelength bands for each pixel.

Spectral pattern reorganization refers to the family of classification procedures that utilizes this pixel-by-pixel spectral information as the basis for automated land cover classification. Techniques like Rough set, Rough-Fuzzy theory, artificial neural network etc are used to classify images. Rough Set theory evolves the concept of data reduction, removing vagueness, discretization, lower and upper bound of the data set. Then rules are generated to classify the image. Fuzzy theory evolves the concept of membership function and membership grade to the objects which are vague in nature. A neural network performs image classification by first undergoing a training session, during which the network is repeatedly, presented a set of input patterns along with the category to which each pattern belongs. Later a new pattern is presented to the network that has not seen before, but which belongs to the same population of the patterns used to train the network. There are two types of classification:

- Unsupervised
- Supervised

A. Unsupervised classification

Unsupervised classifiers do not utilize training data as the basis for classification, rather this family of classifiers involves algorithm that examine the unknown pixel in an image and aggregate them into a number of classes based on the natural grouping or clusters present in the image values [3].

- The basic premise is that values within a given cover type should be closed together in the measurement space whereas data in different classes should be comparatively well separated.
- The classes that results from unsupervised classification are spectral classes because they are based solely on natural grouping in the image values, identity of the spectral classes will not be initially known.
- The analyst must compare the classified data within some form of referenced data to determine the identity and informational value of spectral classes
- Any individual pixel is compared to each discrete cluster to see which one it is closest to.
- A map of all pixels in the image, classified as to which cluster each pixel is most likely to belong, is produced (in

black and white or more commonly in colours assigned to each cluster).

- This then must be interpreted by the user as to what the color patterns may mean in terms of classes, etc. that are actually present in the real world scene; this requires some knowledge of the scene's feature/class/material content from general experience or personal familiarity with the area imaged.

B. Supervised Classification

There are basically three steps involved in a typical supervised classification procedure [3].

- **Training Stage –** In the training stage the analyst identifies representative training areas and develops a numerical description of the spectral attributes of each land cover type of interest in the scene.
- **Classification Stage –** In classification stage, each pixel in the image data set is categorized into the land cover class it most closely resembles. If the pixel is insufficiently similar to any training data set, it is usually labeled unknown. The category labeled assigned to each pixel in this pixel is then recorded in corresponding cell of an interpreter.
- **Output Stage –** After the entire data set has been categorized, the results are presented in the output stage. Being digital in character, the results may be used in number of ways.

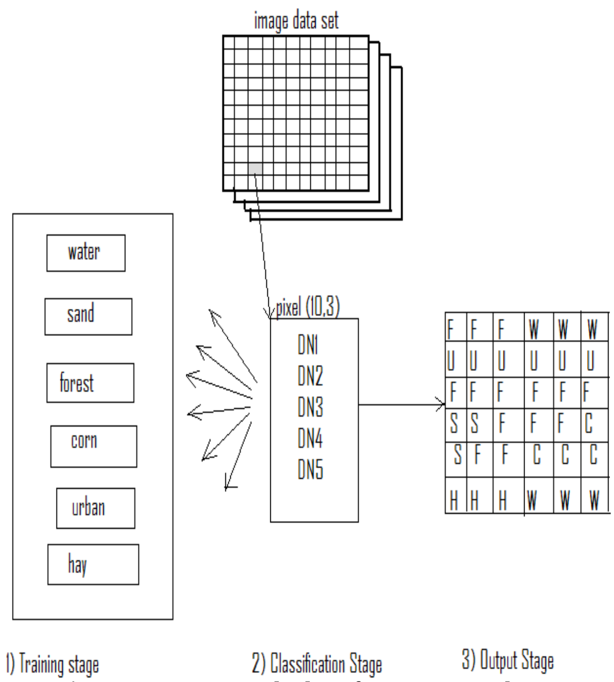


Figure 2: Supervised Classification Procedure.

V. PROPOSED ALGORITHM

The Bacterial Foraging Optimization Algorithm (BFOA) is proposed by Kevin Passino (2002), is a new comer to the family of nature inspired optimization algorithms. Application of group foraging strategy of a swarm of E.coli bacteria in multi-optimal function optimization is the key idea of this new algorithm. Bacteria search for nutrients is a manner to maximize energy obtained per unit time. Individual bacterium also communicates with others by sending signals. A bacterium takes foraging decisions after considering two previous factors. The process, in which a bacterium moves by taking small steps while searching for nutrients, is called chemotaxis. The key idea of BFOA is mimicking chemotactic movement of virtual bacteria in the problem search space.

p : Dimension of the search space,
s : Total number of bacteria in the population,
N_c : The number of chemotactic steps,
N_s : The swimming length,
N_{re} : The number of reproduction steps,
N_{ed} : The number of elimination dispersal events,
P_{ed} : Elimination dispersal probability,
C(i) : The size of the step taken in the random direction specified by the tumble.

Foraging theory is based on the assumption that animals search for and obtain nutrients in a way that maximizes their energy intake E per unit time T spent foraging. Hence, they try to maximize a function like E/T (or they maximize their long-term average rate of energy intake). Maximization of such a function provides nutrient sources to survive and additional time for other important activities (e.g., fighting, fleeing, mating, reproducing, sleeping, or shelter building). Shelter building and mate finding activities sometimes bear similarities to foraging. Clearly, foraging is very different for different species. Herbivores generally find food easily but must eat a lot of it. Carnivores generally find it difficult to locate food but do not have to eat as much since their food is of high energy value. The “environment” establishes the pattern of nutrients that are available (e.g., via what other organisms are nutrients available, geological constraints such as rivers and mountains and weather patterns) and it places constraints on obtaining that food (e.g., small portions of food may be separated by large distances). During foraging there can be risks due to predators, the prey may be mobile so it must be chased and the physiological characteristics of the forager constrain its capabilities and ultimate success.

VI. SIMULATED RESULTS

The proposed algorithm for the satellite image classification so that a number of information about the land cover area can be acquired with the resources and better accuracy. The complete experimental study and accuracy assessment with the result analysis is described in the following sections. Our objective is to use the proposed swarm algorithms as an efficient land cover classifier. For satellite image. We have taken a multi-spectral, multi resolution and multi- sensor image of Alwar area in provided by DTRL-DRDO. The satellite image for 7 different bands is taken (Fig 11.1). These bands are Red, Green, Near Infra Red(NIR), Middle Infra Red (MIR), Radarsat-1 (RS1), Radarsat-2(RS2), and Digital

Elevation Model) DEM. We are having spectral signatures set from seven bands.

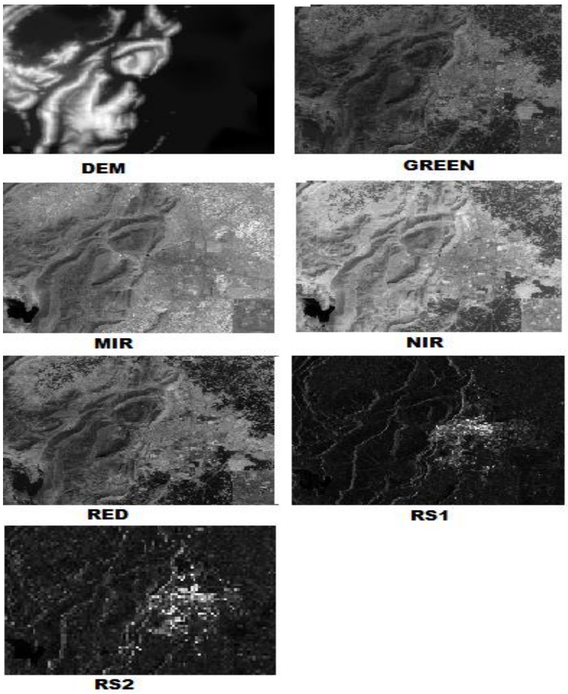
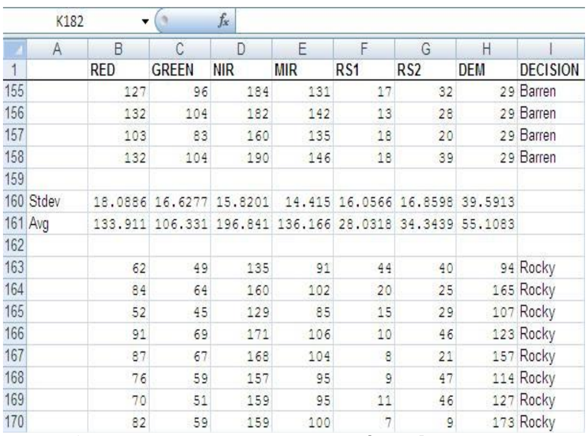


Figure 3: Seven Band Images of Alwar Area.

The training set in excel sheet format for the Alwar area obtained by ERDAS software is as follows.



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	A	B	C	D	E	F	G	H	I
1		RED	GREEN	NIR	MIR	RS1	RS2	DEM	DECISION
155		127	96	184	131	17	32	29	Barren
156		132	104	182	142	13	28	29	Barren
157		103	83	160	135	18	20	29	Barren
158		132	104	190	146	18	39	29	Barren
159									
160	Stdev	18.0886	16.6277	15.8201	14.415	16.0566	16.8598	39.5913	
161	Avg	133.911	106.331	196.841	136.166	28.0318	34.3439	55.1083	
162									
163		62	49	135	91	44	40	94	Rocky
164		84	64	160	102	20	25	165	Rocky
165		52	45	129	85	15	29	107	Rocky
166		91	69	171	106	10	46	123	Rocky
167		87	67	168	104	8	21	157	Rocky
168		76	59	157	95	9	47	114	Rocky
169		70	51	159	95	11	46	127	Rocky
170		82	59	159	100	7	9	173	Rocky

Figure 4: Training Data Set for Alwar Area.

The BFO method implemented in this study has the flexibility to set the number of attributes required to be selected. In this research, ten experiments were conducted to select the best subset starting from 2% to 100% of the available attributes. In each experiment, 100 iterations were executed, and the best subset was selected. The best attribute subsets selected by BFO are presented. The figure shows the selected attribute subsets and the classification performance according to the overall accuracy and kappa measures. The highest overall accuracy and kappa coefficient were observed, in which attributes were selected by the algorithm. Accordingly, this subset was considered the best attribute subset for the data and study area.

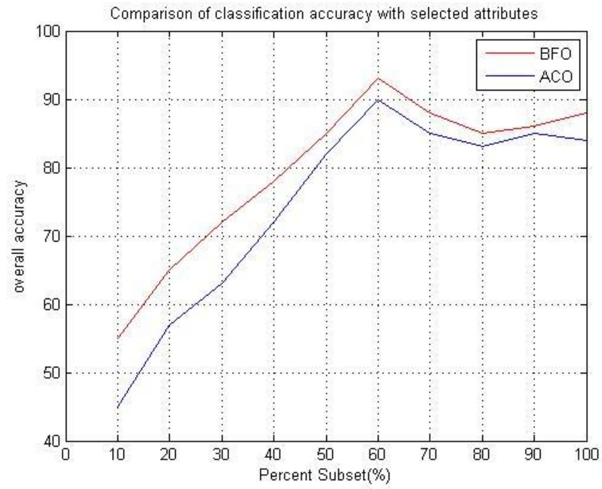

Figure 5: Comparison According to Accuracy.

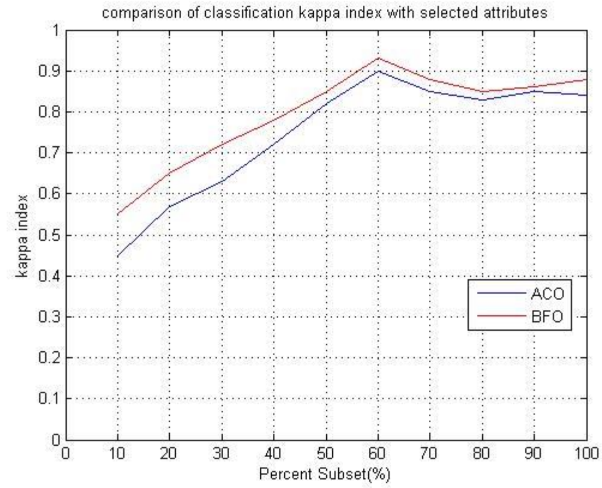

Figure 6: Comparison According to Kappa.

The main goal of feature selection is to reduce overfitting to the training data and to speed up the classification process. It also reduces the redundancy in the information provided by the selected features. Therefore, several feature selection methods have been proposed for various applications. The performance of these algorithms can be affected by the type of application and the datasets used in the analysis. The BFO feature selection method was compared with three well-known methods to evaluate its performance and further justify its selection in the current study. Population-based optimization algorithms such as BFO based method have attracted a lot of attention. This method attempts to achieve better solutions by applying knowledge from previous iterations.

VII. CONCLUSION

By using this approach we are able to classify the satellite image according to different areas like water, urban, vegetation, barren and rocky region with different colors assigned to each feature's pixels. It can be concluded from the results that the theory of BFO can be efficiently used to design classificatory algorithm whereas originally it was used for solving the optimization problems only. This new method to classify remote-sensing data by using BFO has been tested with several images. Accurate results have been obtained in these images, two of which have been discussed in this paper. Mathematical morphology operations have also been used to refine the features in the image. The proposed algorithm shows promising results as all the features have been identified using this algorithm accurately irrespective of type of satellite image being processed. The various features present in the image were refined by using Mathematical morphology Operation.

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