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The Classification Accuracy of Multiple-Metric Learning Algorithm on Multi-Sensor Fusion

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Abstract—this paper focuses on two main issues; first one is the impact of Similarity Search to learning the training sample in metric space, and searching based on supervised learning classification. In particular, four metrics space searching are based on spatial information that are introduced as the following; Chebyshev Distance (CD); Bray Curtis Distance (BCD); Manhattan Distance (MD) and Euclidean Distance(ED) classifiers. The second issue investigates the performance of combination of multi-sensor images on the supervised learning classification accuracy. QuickBird multispectral data (MS) and panchromatic data (PAN) have been used in this study to demonstrate the enhancement and accuracy assessment of fused image over the original images. The supervised classification results of fusion image generated better than the MS did. QuickBird and the best results with ED classifier than the other did.

Index Terms— Similarity Search, Metric Spaces, Distance Classifier, Image Fusion, Classification, Accuracy Assessment.

I. INTRODUCTION

In the aspect of digital image classification, the classification is defined as, "information of extracting process which analyses the adopted spectral signatures by using a classifier and then assigns the spectral vector of pixels to categories according to their spectral". Many factors affect the accuracy of image classification [1] and the quality of land cover maps is often perceived as being insufficient for operational use [2]. In the literature there are two broad approaches of classification procedure are used in classifying images. One is referred to as supervised classification and the other unsupervised classification. In the case of unsupervised classification means by which pixels in the image are assigned to spectral classes without the user having foreknowledge of training samples or a-prior knowledge of the area. While In the case of supervised classification, requires samples of known identity (training samples) to construct a capable model of classifying unknown samples. In the literature, most of the attention has been given on improving the accuracy of the classification process by acting mainly at the following three levels: 1) data representation; 2) discriminate function model; and 3) criterion on the basis of which the discriminate functions are optimized [3]. These works are based on an essential assumption that is the samples used to train the classifier which are statistically representatives of the classification's problems to solve. However, the process of collection of training samples is not trivial, because the human intervention is subject to errors and costs in terms of both time and money.

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Therefore, the quality and the quantity of such samples are a key to successful classification, because they have a strong impact on the performances of the classifier [1]. A sufficient number of training samples is generally required to perform a successful classification and the samples need to be well distributed and sufficiently representative of the land cover classes being evaluated [4-5].

In order to address the aforementioned problems, in the recent literature, different promising approaches have been proposed for image classification, which has a growing interest in developing strategies for the machine learning of the training samples. In the machine learning field, the active learning approach represents an interesting solution to face this problem. Considering a small and suboptimal initial training set, few additional samples are selected from a large amount of unlabeled data (learning set). These samples are labelled by the human expert and then added to the training set. The entire process is iterated until a stopping criterion is satisfied. The aim of active learning is to rank the learning set according to an opportune criterion that allows selecting the most useful samples to improve the model, thus minimizing the number of training samples necessary to maintain discrimination capabilities as high as possible.

The common denominator of active learning methods introduced up-to-now in the literature it means they are all formulated in the spectral domain and all ignore the spatial dimension characterizing images to classify. However, in the remote sensing literature, it has been demonstrated how the integration of spectral and spatial information is important for solving problems in different contexts. For instance, classification problems are faced in different works by adopting different approaches, such as solutions based on using filter banks [6], a kernel-based method [7], morphological filters [8], thresholding the magnitude of the spectral [9], fuzzy statistical similarity measure [10], Images acquired at different times can be used for change detection problems, as done for data acquired by different sensors [11], and optical images using linear spatial-oriented operators [12]. A natural use of spatial information is represented by image registration techniques. For instance, in [13] spatial and spectral information are combined for this purpose, finally textural metrics in [14].

In the study the developed system User Graphic Interface UGI ALwassaiProcess software was designed to automatic classification by selecting any number and size of regions that will be the training data of the test image. This is the crucial program for the image of classification, this deals with how to select the training data automatically which describes the best pattern and by this way allow us to determine the interesting class of user of image. The program offers the selection of any size of the training data; it means that the user can decide the increase of the successful of clas-

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sification by this experiment. This study focusing on two main issues, first one is about the impact of spatial information; it can be useful in the search of similarity's process through training sample collection in different metric space searching based on supervised learning classification of remote sensing images. In particular, four metrics space searching are introduced as the following: Chebyshev Distance (CD); Bray Curtis Distance (BCD); Manhattan Distance (MD) and Euclidean Distance(ED) classifiers. All of the image classification speeds have been calculated using the same training data for each test image. The second issue investigates the performance of combination multi-sensor images on the classification accuracy. To investigate the performance of these algorithms, we conducted an experimental study based on two VHR images acquired by QuickBird. The remaining sections are organized as follows. Section 2 describes metric spaces; Section 3 describes multiple metric classifiers; section 4 presents the data sets used in the experimental analysis and classification results of fused image and Section 5 conclusions. The computer hardware used to record the image classification algorithm speeds are an Intel® Core ™ i5-245OM CPU@ 2.50 GHz with Turbo Boost 3.10 GHz and 4.00GB RAM installed. The ALwassaiProcess software was running on operating system Microsoft Windows 7 64-bit respectively.

II. METRIC SPACES

A metric space is a pair(X, d), where X the domain of objects and d is the total distance function $d : X \times X \rightarrow \mathbb{R}^d$ is a distance metric measuring the dissimilarity $d(x; y)$ between any two objects $x; y \in X$. The distance function must satisfy the following properties objects in$X$: strict positiveness $(d(x,y) > 0 \Leftrightarrow x \neq y)$, symmetry$(d(x,y) = d(y,x))$, identity $(d(x,y) = 0 \ if \ x = y)$ and triangle inequality $(d(x,z) \leq d(x,y) + d(y,z))$.

The database or collection of objects is a finite subset $U \subseteq X$ of size$|U| = n$. Search Query such as Proximity query, Similarity query, Dissimilarity query …etc. Since, the main focus here is to decide on the training sample from the data set, we will focus on the measure of similarity query. The Similarity query has three main queries of interest for a collection of objects in a metric space:

- **i.** Range query that retrieves all the objects: $x \in X$ within a radius r of the query q, that is $R(q,r) = \{ x \in X \ \forall \ d(q,x) \leq r \}$.
- **ii.** *Nearest neighbor search*, that retrieves the most similar object to the query q, that is $NN(q) = x, x \in X, \forall y \in X, d(q,x) \leq d(q,y)$.
- **iii.** *K-nearestneighbours search*, a generalization of the nearestneighbour search, retrieving the set $A \subseteq X$ such that $|A| = k \ and \ \forall \ x \in A, y \in X - A, d(q,x) \leq d(q,y)$.

In any case, the distance function is the unique information that can be used in the search operation. Thus, the basic way of implementing these operations is to compare all the objects in the collection against the query.

Selection strategy Methods for searching in metric spaces can be classified in pivot-based methods and clustering-based methods [15]. Pivot-based search methods choose a subset of the objects in the collection that are used as pivots. The index stores the distances from each pivot to each object in the collection in adequate data structures. Given a query (q, r), the distances from the query q to each pivot are computed, and then some objects of the collection can be directly discarded using the triangle inequality and the distances pre-computed during the index building phase. Clustering-based techniques split the metric space into a set of clusters each represented by a cluster centre. Given a query, whole regions can be discarded from the search result using the distance from their centre to the query and the triangle inequality. The partitioning of sub set in is called the criterion functions can be defined by different way. Let $X \subseteq D$ in $M = (D, d)$ three basic partitioning principles have been defined as the following:

1) Ball Partitioning:

Inner set: $\{ x \in X \mid d(p,x) \leq dm \}$,

Outer set: $\{ x \in X \mid d(p,x) > dm \}$,

2) Generalized Hyper-Plane Partitioning:

$\{ x \in X \mid d(p1,x) \leq d(p2,x) \}$,

$\{ x \in X \mid d(p1,x) > d(p2,x) \}$ and,

3) Excluded Middle Partitioning:

Inner set: $\{ x \in X \mid d(p,x) \leq dm \}$, Outer set: $\{ x \in X \mid d(p,x) > dm \}$, $\{ x \in X \mid d(p1,x) \leq d(p2,x) \}$, $\{ x \in X \mid d(p1,x) > d(p2,x) \}$.

The definition of the distance function depends on the type of the objects that we are managing. As the case of images have two coordinate spaces, the pixels values are treated as vectors in a multi -dimensional space by mapping each feature to a value of a particular dimension. The concept of vectors in a multi-dimensional space offers, means to calculate distances of two pixels by computing the distance of the corresponding feature-vectors Search structures for vector spaces, so-called spatial access methods, effectively exploit the ordering of feature values of a dimension to find similar objects[16].

III. MULTIPLE METRIC CLASSIFIERS

The family Minkowski distances to distinguish between any two classes will be used in vector space of image classification. The generic form of the Minkowski distance metric is the following:

$$\text{distance}_p\left(\vec{x}^{(0)}, \vec{x}^{(f)}\right) = \left(\sum_{i=1}^{n} \left|x_i^{(f)} - x_i^{(0)}\right|^p\right)^{1/p} \quad (1.1)$$

Where $p \in \mathbb{R}^N$ is the power of the metric in multidimensional N, is the $\vec{x}^{(0)}$ the initial point (the source point), $\vec{x}^{(f)}$ is the final point, and n is the shared dimension of the points.

In order to determine how similar or different each class from unknown pixel to the mean vector of training data in the multi-sensor remote image. In the supervised classification, the acquisition of ground truth data for training and assessment is a critical component in process. In this study the training data will be extracted by having certain regions and they will have their RGB values represented by the mean red, the mean blue and the mean green values separately. Supposing the size of the region selected is $b \times c$ pixels, the colour RGB values will be represented by (1.2).

$$\vec{\mu}_{i,k} = \frac{1}{b \times c} \sum_{p=1,q=1}^{p=b,q=c} \vec{x}_k(p,q) \quad (1.2)$$

Where

$\vec{\mu}_{i,k}$ = the mean vector of training pixel value for each class k in query of the $b \times c$ region.

$\vec{x}_k$ = the vector of training pixel value at position (p,q)

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within the region of class k in query.
The mean vector of training data will just be the centre value in vector space of the b × c pixels region. The following notations will be used: $\mu_{i,k}^{(0)}, i = 1, \ldots n$ are the means vectors for each class k in query, $x_{ik}^{(f)}$ is the position of the test pixel value in an image to be classified. The criterion function corresponding of the ball partitioning will be represented by (1.3).

$$x_{i,k}^{(f)} \in X \; if \; d_{i,k}\left(\vec{\mu}_{i,k}^{(0)}, \vec{x}_{i,k}^{(f)}\right) < d_{n,k}\left(\vec{\mu}_{nk}^{(0)}, \vec{x}_{nk}^{(f)}\right) \quad for\; all\; n \neq i \qquad (1.3)$$

This study implied different distance measurements considered as the classification strategy in the metric space and will be used to discriminate of a certain pixel, or block, from each of the defined *k* classes in the training set as the following:

A. Manhattan Distance Classifier (MD)

It is also known as City Block distance, boxcar distance, absolute value distance and taxicab distance. The discriminate function for MD classifier represents distance between points in a city road grid. It examines the absolute differences between coordinates of a pair of objects. To compute the set of the absolute differences between MD of the unknown pixel to each of the class means, defined in vector form as follows and has the unit circle detailed in [16]:

$$d_{i,k}\left(\vec{\mu}_{i,k}^{(0)}, \vec{x}_{i,k}^{(f)}\right) = \left(\sum_{i=1}^{n} \left|x_{i,k}^{(f)} - \mu_{i,k}^{(0)}\right|^{1}\right)^{1/1} = \left|x_{1,k}^{(f)} - \mu_{1,k}^{(0)}\right| + \ldots + \left|x_{n,k}^{(f)} - \mu_{n,k}^{(0)}\right| \qquad (1.4)$$

B. Euclidean Distance Classifier (ED)

The ED is a particular case of Minkowski sometimes is also called Quadratic Mean takes the following form and has the unit circle detailed in [16]:

$$d_{i,k}\left(\vec{\mu}_{i,k}^{(0)}, \vec{x}_{i,k}^{(f)}\right) = \left(\sum_{i=1}^{n} \left|x_{i,k}^{(f)} - \mu_{i,k}^{(0)}\right|^{2}\right)^{1/2} = \sqrt{\left|x_{1,k}^{(f)} - \mu_{1,k}^{(0)}\right|^{2} + \ldots + \left|x_{n,k}^{(f)} - \mu_{n,k}^{(0)}\right|^{2}} \qquad (1.5)$$

C. Chebychev Distance Classifier (CD)

CD is also called Maximum value distance. Other name: Tchebyschev Distance (due to translation). It examines the absolute magnitude of the differences between coordinates of a pair of objects. CD classifier defined in vector form as the following (the unit circle detailed in [16]:

$$d_{i,k}\left(\vec{\mu}_{i,k}^{(0)}, \vec{x}_{i,k}^{(f)}\right) = \lim_{p\to\infty}\left(\sum_{i=1}^{n} \left|x_{i,k}^{(f)} - \mu_{i,k}^{(0)}\right|^{p}\right)^{1/p} = max_{i,k}\left\{\left|x_{1,k}^{(f)} - \mu_{1,k}^{(0)}\right|, \ldots, \left|x_{n,k}^{(f)} - \mu_{n,k}^{(0)}\right|\right\} \qquad (1.6)$$

D. Bray Curtis Distance BCD

BCD sometimes is also called Sorensen distance is a normalization method. It views the space as grid similar to the city block distance. The BCD has a nice property that if all coordinates is positive; its value is between zero and one. Zero BC represent exact similar coordinate. If both objects are in the zero coordinates, the BCD is undefined. The normalization is done using absolute difference divided by the summation. BCD will be represented by (1.7).

$$d_{i,k}\left(\vec{\mu}_{i,k}^{(0)}, \vec{x}_{i,k}^{(f)}\right) = \frac{\sum_{i=1}^{n}\left|x_{i,k}^{(f)} - \mu_{i,k}^{(0)}\right|}{\sum_{i=1}^{n} x_{i,k}^{(f)2} + \sum_{i=1}^{n} \mu_{i,k}^{(0)2}} \qquad (1.7)$$

IV. EXPERIMENTAL RESULTS

4.1 Test Data Sets

The images that are going to be fused and classified in this study are downloaded from http://studio.gge.unb.ca/UNB/images. These remote sensing images are taken by QuickBird satellite sensor which collects one panchromatic band (450-900 nm) of the 0.7 m resolution and blue (450-520 nm), green (520-600 nm), red (630-690 nm), near infrared (760-900 nm) bands of the 2.8 m resolution. The coverage of the images was over the Pyramid area of Egypt in 2002. Before the image fusion, the raw MS were resampled to the same spatial resolution of the PAN in order to perform image registration. The test images of size 864 by 580 at the resolution of 0.7 m are cut from the raw images. The classification is tested to demonstrate the enhancement and accuracy assessment on resulted image fused by using the SF algorithm developed and tested with their effectiveness evaluated in [17-25]. Fig.1 displays both The QuickBird MS and PAN images, along with fusion image.

Fig. 1: Experimental Test Images Over The Pyramid Area Of Egypt In 2002. (a) Quickbird Data: MS (b) Quickbird: PAN (c) The Resulted of Fused Image.

4.2 Supervised Distance Classifier

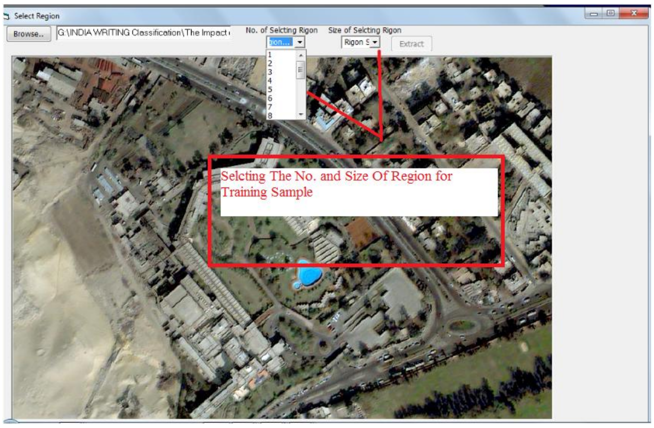
In the supervised classification, the acquisition of ground truth data for training and assessment is a critical component in process. In this study the training data will be extracted by having certain regions selected as decried below. The classification consists of the following steps:

- **Step 1**: Select the number and the size of regions that will be the training data the image as shown in Fig.2a. The author has selected twelve classes as shown in Fig.2b, and the size of each region selecting for the training data is 4 × 4 pixels was chosen.
- **Step 2**: experts the image; experts training data; and select distance classifier methods as shown in Fig.3.
- **Step 3**: Apply the distance between a pixel i in the image and every

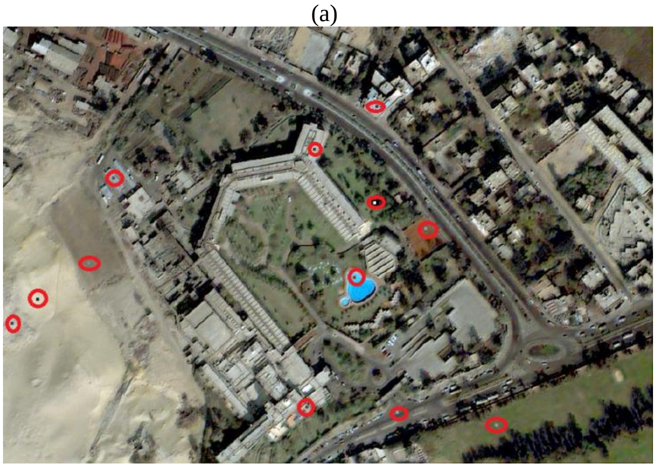
reference class k as shown in Fig.4.

- **Step 4**: Assign each pixel to the reference class k that has the smallest distance between pixel i and reference class k. for each pixel i = 1 to n, find the reference class k such that Distance is the minimum for all k and finally get the result as shown in Fig.5.

- **Step 5**: selected different five regions of each reference class *k* for the accuracy assessment of image classification as shown in Fig.6.
- **Step 6**: the accuracy assessment of image classification as shown in Fig.7.



(a)



(b)

Fig.2: Illustrate Step 1: Select the Number and Size of Regions for Training Data the Test Image

4.3 Classification Results Of Fused Image

To evaluate the performance of the proposed active learning strategies the four multiple metrics classifier were applied for both MS QuickBird and fusion data after the fusion process. To the description of classification error, it is necessary to configure the error matrix and decide the measurements. In this study, as limited time, we focus the accuracy assessment of image classification only on the Overall accuracy. For such purpose, we first selected different five regions that have a 4×4 size for each reference class set is shown in Fig.2b. Table (1- 4) and Table (5-8) list the error matrix for both classified results, respectively. The overall accuracy results for MS classified are 84.24%, 87.26%, 84.60% and 86.63% by BCD, ED, MD and CD classifiers respectively. For fused image classified results are 89.71%, 91.48%, 90.85% and 90.51% By BCD, ED, MD and CD classifiers respectively. In general, the supervised classification results of fusion image generated better than did the MS QuickBird and the best results with ED Classifier than the other did. Fig. 8 show the classified results for fusion image and MS QuickBird image by the four metrics. Fig.9 show the classified results for some classes set with its histogram.

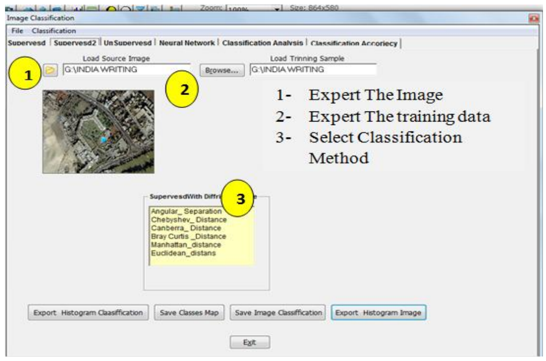


Fig.3: Illustrate Step 2: the Automatic Classification Process: Experts The Image; Experts Training Data; And Select Classifier Methods.

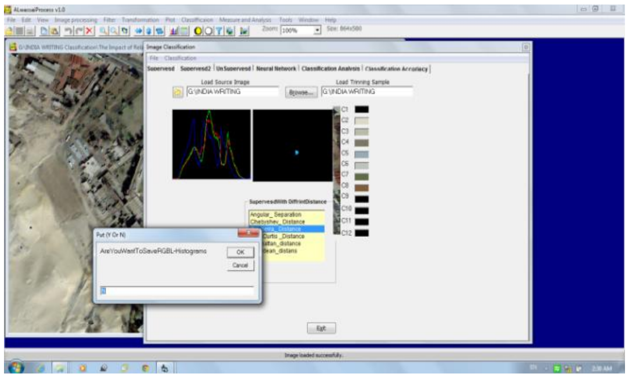


Fig.4: Illustrate Step 3: Apply the Distance Between a Pixel in The Image and Every Reference Class.

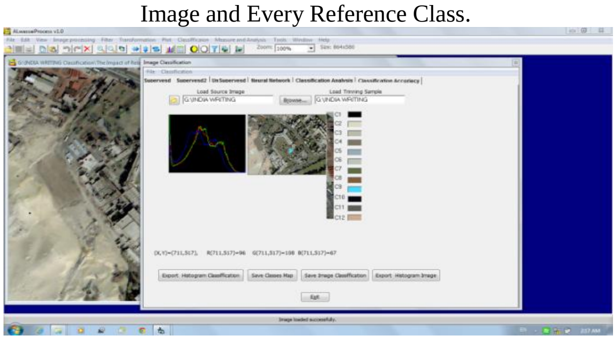


Fig.5: Illustrate Step 4: Assign Each Pixel To The Reference Class K And Finally Get The Result.

Fig.6: Illustrate Step 5.

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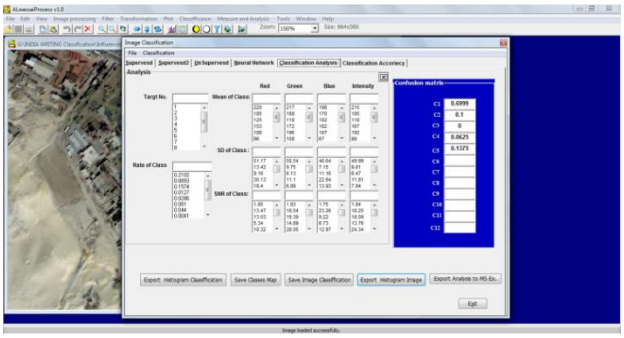

Fig7: Illustrate Step 6: The Accuracy Assessment Of Image Classification.

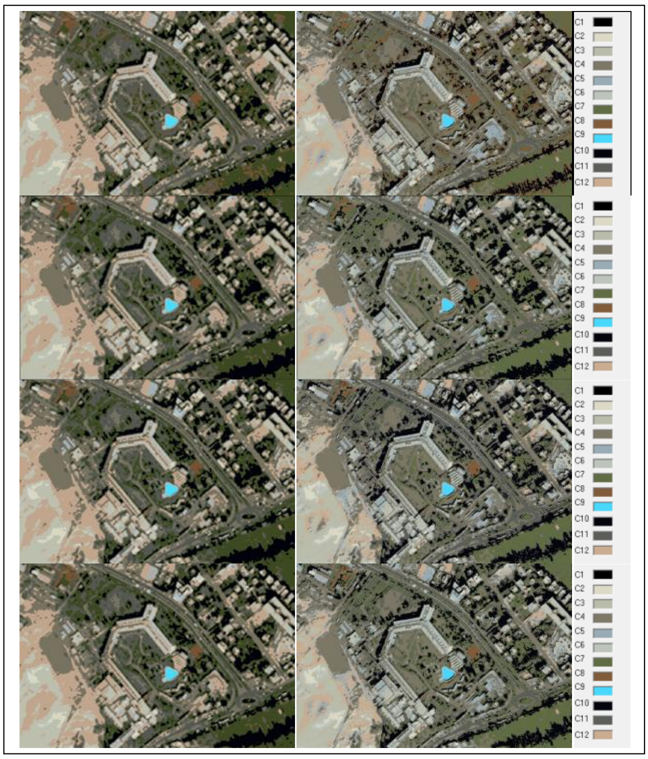

Fig.8: The Left Side Classified Result Of MS Quickbird And The Right Side Classified Result Of Fusion Image With Colour Code Of Each Land Class from Top to Down By: BCD, CD, ED and MD Classifiers respectively.

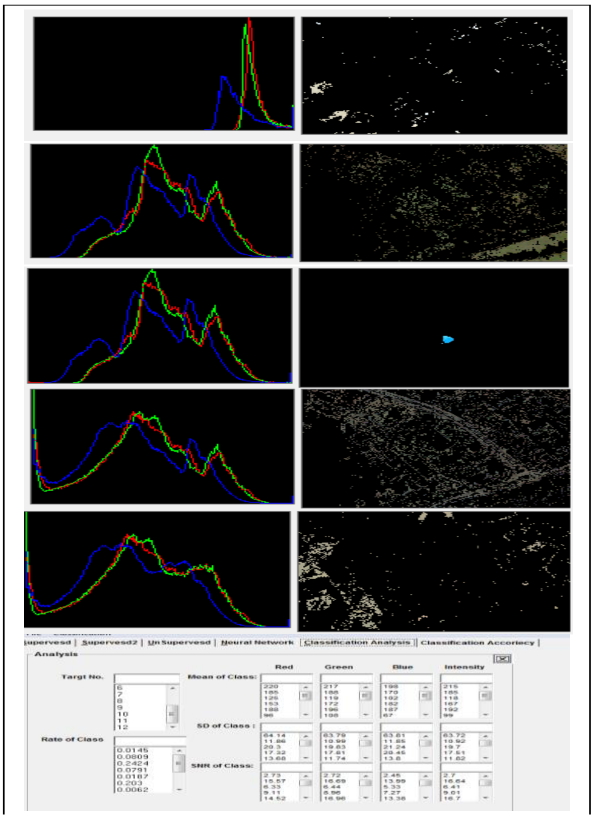

Fig.9: Illustrate the Classified Results for Some Classes Set with Its Histogram.

Table (1): Error Matrix Classified Result for MS QuickBird By BCD Classifier

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	R.Total
C1	**0.9749**				0.025								0.9999
C2	0.025	**0.7499**			0.175						0.05		0.9999
C3			**0.9999**										0.9999
C4			0.0781	**0.9218**									0.9999
C5	0.0125	0.275		0.0375	**0.6749**								0.9999
C6						**0.8749**				0.125			0.9999
C7							**0.9999**						0.9999
C8								**1**					1
C9						0.025	0.0875		**0.8874**				0.9999
C10			0.3624			0.075				**0.5624**			0.9998
C11	0.0125	0.1125	0.1625	0.05		0.0125				0.0125	**0.6374**		0.9999
C12	0.025		0.0375	0.0625	0.05							**0.8249**	0.9999
C. Total	1.0499	1.1374	1.6404	1.0718	0.9249	0.9874	1.0874	1	0.8874	0.6999	0.6874	0.8249	11.9988
Overall Accuracy	**0.9749**	**0.7499**	**0.9999**	**0.9218**	**0.6749**	**0.8749**	**0.9999**	**1**	**0.8874**	**0.5624**	**0.6374**	**0.8249**	**0.842358333**

Table (2): Error Matrix Classified Result for MS QuickBird By ED Classifier

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	R. Total
C1	**0.9749**				0.025								0.9999

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C2	0.0375	**0.7874**			0.1625						0.0125		0.9999
C3			**0.9999**										0.9999
C4			0.0781	**0.9218**									0.9999
C5		0.25		0.05	**0.6999**								0.9999
C6						**0.8999**					0.1		0.9999
C7							**0.9999**						0.9999
C8								**1**					1
C9									**0.9624**	0.0375			0.9999
C10			0.2874							**0.7124**			0.9998
C11	0.0375	0.0375	0.2125							0.025	**0.6874**		0.9999
C12	0.0125		0.0375	0.0875	0.0375							**0.8249**	0.9999
C. Total	1.0624	1.0749	1.6154	1.0593	0.9249	0.8999	0.9999	1	0.9624	0.7749	0.7999	0.8249	11.9988
Overall Accuracy	0.9749	0.7874	0.9999	0.9218	0.6999	0.8999	0.9999	1	0.9624	0.7124	0.6874	0.8249	0.872566667

Table (3): Error Matrix Classified Result for MS QuickBird By MD Classifier

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**R. Total**
C1	**0.9749**				0.025								0.9999
C2	0.025	**0.7499**			0.175						0.05		0.9999
C3			**0.9999**										0.9999
C4			0.1093	**0.8906**									0.9999
C5		0.2999		0.0375	**0.6624**								0.9998
C6						**0.8999**				0.1			0.9999
C7							**0.9999**						0.9999
C8								**1**					1
C9						0.0375			**0.9624**				0.9999
C10			0.3499			0.0625				**0.5874**			0.9998
C11	0.0125	0.1125	0.175	0.0375		0.0125				0.0125	**0.6374**		0.9999
C12	0.025		0.0375	0.0875	0.0625							**0.7874**	0.9999
C. Total	1.0374	1.1623	1.6716	1.0531	0.9249	1.0124	0.9999	1	0.9624	0.6999	0.6874	0.7874	11.9987
Overall Ac-curacy	0.9749	0.7499	0.9999	0.8906	0.6624	0.8999	0.9999	1	0.9624	0.5874	0.6374	0.7874	0.846008333

Table (4): Error Matrix Classified Result for MS QuickBird By CD Classifier

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**R. Total**
C1	**0.9999**												0.9999
C2		**0.8499**			0.15								0.9999
C3			**0.9999**										0.9999
C4			0.1406	**0.8593**									0.9999
C5		0.3624		0.0625	**0.5749**								0.9998
C6						**0.9499**				0.05			0.9999
C7							**0.9999**						0.9999
C8								**1**					1
C9									**0.9999**				0.9999
C10			0.3124							**0.6874**			0.9998
C11		0.0125	0.25								**0.7374**		0.9999
C12				0.2125	0.05							**0.7374**	0.9999
C. Total	0.9999	1.2248	1.7029	1.1343	0.7749	0.9499	0.9999	1	0.9999	0.7374	0.7374	0.7374	11.9987
Overall Accuracy	0.9999	0.8499	0.9999	0.8593	0.5749	0.9499	0.9999	1	0.9999	0.6874	0.7374	0.7374	0.866316667

Table (5): Error Matrix Classified Result for Fusion Image By BCD Classifier

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**R. Total**
C1	0.9499	0.025			0.025								0.9999
C2		**0.8874**			0.1						0.0125		0.9999
C3			**0.9999**										0.9999
C4			0.0468	**0.8906**							0.0625		0.9999
C5	0.1				**0.8999**								0.9999
C6						**0.8124**	0.1125			0.075			0.9999
C7							**0.9999**						0.9999
C8								**1**					1
C9									**0.9999**				0.9999
C10			0.3624							**0.6374**			0.9998
C11			0.15								**0.8499**		0.9999
C12				0.1625								**0.8374**	0.9999
C. Total	1.0499	0.9124	1.5591	1.0531	1.0249	0.8124	1.1124	1	0.9999	0.7124	0.9249	0.8374	11.9988
Overall Accuracy	**0.9499**	**0.8874**	**0.9999**	**0.8906**	**0.8999**	**0.8124**	**0.9999**	**1**	**0.9999**	**0.6374**	**0.8499**	**0.8374**	**0.89705**

Table (6): Error Matrix Classified Result for Fusion Image By ED Classifier

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C 8**	**C9**	**C10**	**C11**	**C12**	**R. Total**
C1	**0.96**	0.02			0.01								0.9999

	24	5			25								
C2		**0.8749**			0.1						0.025		0.9999
C3			**0.9999**										0.9999
C4			0.1093	**0.8906**									0.9999
C5		0.1			**0.8999**								0.9999
C6						**0.9499**				0.05			0.9999
C7							**0.9999**						0.9999
C8								**1**					1
C9									**0.9999**				0.9999
C10			0.2375							**0.7624**			0.9999
C11			0.1625								**0.8374**		0.9999
C12				0.2								**0.7999**	0.9999
C. Total	0.9624	0.9999	1.5092	1.0906	1.0124	0.9499	0.9999	1	0.9999	0.8124	0.8624	0.7999	11.9989
Over-all Accu-racy	**0.9624**	**0.8749**	**0.9999**	**0.8906**	**0.8999**	**0.9499**	**0.9999**	**1**	**0.9999**	**0.7624**	**0.8374**	**0.7999**	**0.914758**

Table (7): Error Matrix Classified Result for Fusion Image By MD Classifier

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	R. Total
C1	**0.9499**	0.025			0.025								0.9999
C2		**0.8874**			0.1						0.0125		0.9999
C3			**0.9999**										0.9999
C4			0.1093	**0.8906**									0.9999
C5		0.1			**0.8999**								0.9999
C6						**0.9749**				0.025			0.9999
C7							**0.9999**						0.9999
C8								**1**					1
C9									**0.9999**				0.9999
C10			0.3374							**0.6624**			0.9998
C11			0.175								**0.8249**		0.9999
C12				0.1875								**0.8124**	0.9999
C.Total	0.9499	1.0124	1.6216	1.0781	1.0249	0.9749	0.9999	1	0.9999	0.6874	0.8374	0.8124	11.9988
Overall Accuracy	**0.9499**	**0.8874**	**0.9999**	**0.8906**	**0.8999**	**0.9749**	**0.9999**	**1**	**0.9999**	**0.6624**	**0.8249**	**0.8124**	**0.908508**

Table (8): Error Matrix Classified Result for Fusion Image By CD Classifier

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	R.Total
C1	**0.9374**	0.0375			0.025								0.9999
C2		**0.8749**			0.1125						0.0125		0.9999
C3			**0.9999**										0.9999
C4			0.0937	**0.875**							0.0312		0.9999
C5		0.0875			**0.9124**								0.9999
C6						**0.9874**				0.0125			0.9999
C7							**0.9999**						0.9999
C8								**1**					1
C9									**0.9999**				0.9999
C10			0.3124							**0.6874**			0.9998
C11			0.2								**0.7999**		0.9999
C12				0.2	0.0125							**0.7874**	0.9999
C. Total	0.9374	0.9999	1.606	1.075	1.0624	0.9874	0.9999	1	0.9999	0.6999	0.8436	0.7874	11.9988
Overall Accuracy	**0.9374**	**0.8749**	**0.9999**	**0.875**	**0.9124**	**0.9874**	**0.9999**	**1**	**0.9999**	**0.6874**	**0.7999**	**0.7874**	**0.905125**

V. CONCLUSION

Results of learned multiple metric classifiers for MS QuickBird Classified image has the lowest accuracy in comparison of the Fused Image Classified Result. When two data sets together (MS and PAN images) combined by using the SF algorithm in feature-level image fusion, confusion problem was solved effectively. Another advantage of feature-level image fusion is its ability to deal with ignorance and missing information. Out of all four learned multiple metric classifiers the Euclidean Classifier has higher accuracy than other supervised distance classifiers.

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