Machine Learning-Based Classification of Remote Sensing Images Using Hybrid Model

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***Abstract*- A machine learning algorithm to improve classification images from remote sensing. The strengths of machine learning include the capacity to handle data of high dimensionality. In proposed method remote sensing images from WHU-RS19, AID, UC-MERCED datasets are taken. for enhancement non-local mean filter, gaussian filter, haze removal procedure is applied on green channel of images. The classification task is performed by extraction of feature like Linear Binary pattern, Different Invariant, Segmentation Fractal, Tamura, Gray-level Co-Matrix using quadratic SVM classifier. The result obtains using proposed method by is observe to be better than other methods.**

Keywords: SVM, Texture Feature, all-over accuracy

1. Introduction

Scene classification is a process of assigning a semantic label to remote sensing (RS) images. It is one of the crucial tasks in aerial image understanding. Aerial scene classification is possible due to the existence of several RS images datasets collected from satellites, aerial systems, and unmanned aerial vehicles (UAV). Remote sensing image classification has located its utilization in many fields: military, traffic observation, and disaster monitoring. The problem of aerial scene classification is complex because the composition of remote sensing images is compound, and it is rich in features: space and texture. This is the reason for developing numerous scene classification methods. The problem of aerial scene classification is complex because the composition of remote sensing images is compound, and it is rich in features: space and texture. This is the reason for developing numerous scene classification methods. Remote sensing image classification methods that rely on feature extraction can be categorized in one of the following groups: methods that use low-level image features, methods that use mid-level image features and methods that utilize high-level image representation. Methods using low-level image features operate on aerial scene classification with low-level visual descriptors: spectral, textural, structural [1,2,3].

Convolutional Neural Networks (CNNs) have been applied in computer vision and machine learning tasks throughout the last years, primarily due to their capacity to extract proper high-level semantic information. One can observe that they have been successfully applied in distinct applications, such as action and biometric recognition, as well as medical image analysis, to cite a few. Additionally, several research competitions (e.g., IARPA and GRSS) fostered the development of such techniques as they are capable of robustly classifying image datasets. Despite the recent success reached by CNN architectures, there are some real-world applications, such as biometrics, spoofing, noisy and adversarial scenarios in which they still do not perform well. In such tasks, one might observe that the use of CNN ensembles might create more effective models that combine complementary pieces of information [4,5,6].

A remote sensing image typically covers a large range of lands, in which many kinds of objects exist, such as bridge, car, pond, forest, and grassland. This increases the difficulty of scene classification since the label of the scene could be ambiguous with respect to the primary object and the secondary objects. Hence, the feature representation of the image is the key factor that determines the performance of remote sensing scene classification. In an ideal case, the feature representation is expected to be highly correlated with the primary object, and less correlated with the second objects. Conventionally, hand-crafted features have been well studied to improve the classification accuracy, including global features [7,8,9].

Computational time and memory utilization have become important advancements in computer vision. Classifiers, on the other hand, are needed to have significant generalization ability while also producing high performance. A growing area of study for remote sensing imagery characterization is noted. Extra remote sensing image analysis execution measures have been found using the hybrid-based method, which is an additional step from data mining strategies. Classification of images is an important use of computer vision in this field. Our main goal is to advance machine learning methods for remote sensing picture categorization. The information included in satellite pictures, such as buildings, landscapes, deserts, and structures, is categorized and analyze throughout time using images including satellite imagery. Due to the variety of remote sensing picture classification systems, we choose to use the generic phrase of "remote sensing image classification" rather than "remote sensing image classification technology." In general, scholars worked to categorize remote sensing pictures by labelling each pixel with a semantic class since the spatial resolution of remote sensing images is extremely poor, which is comparable to how things are represented in the early scientific literatures. Furthermore, this is still an ongoing research subject for multispectral and hyperspectral remote sensing picture analysis [10,11,12].

2. Related Work

A SVM consists in solving the convex quadratic programming problem, for a given kernel k(x,y) and a given value of the regularization parameter c. Even if efficient numerical techniques exist to solve generic problems of this type, specially designed algorithms have been studied to solve problem. These algorithms exploit the properties of problem, such as the sparseness and uniqueness of its solution, to overcome some of its drawbacks, in particular the fact that a lxl matrix containing the values k(x, x3) should be kept in memory. This last fact means that the memory requirements grow as 12, where 1 is the size of the training set. This makes it possible to efficiently found the solution of problem even for training sets of hundreds of thousands of patterns [13].

Machine learning classification techniques like, Random Forest (RF), Classification and Regression Trees (CART) and Support Vector Machine (SVM) along with the Maximum likelihood classification (MXL) for crop classification using Google earth Engine and ERDAS imagine for IARI farm land using high resolution Sentinel-2 MSI (10m resolution) data and ground truth collected using smartphone based android application.

Around 100 crop fields (~400 Hectare) in IARI were analyze. Smart phone-based ground truth data were collected. The best cloud free image of Sentinel 2 MSI data (5 Feb 2016) was used for classification using automatic filtering by percentage cloud cover property using the GEE. Polygons as feature space was used as training data sets based on the ground truth data for crop classification using machine learning techniques.

Post classification, accuracy assessment analysis was done through the generation of the confusion matrix (producer and user accuracy), kappa coefficient and F value. In this study it was found that using GEE through cloud platform, satellite data accessing, filtering and pre-processing of satellite data could be done very efficiently [14].

Remote sensing images were classified using a per-field classification approach. Many previous studies have shown that efficiency of Remote sensing images classification can be improved Classification was done using the SVM classifier. Support vector machine (SVM) became popular for solving problems in classification, regression. An important property of support vector machines is that the determination of the model parameters corresponds to a convex optimization problem, and so any local solution is also a global optimum. The SVM is a decision machine and, unlike ANNs, does not provide posterior probabilities [15].

Although, SVM has given efficient results in classification of remotely sensed data however SVM kernel functions gives varied result upon input image changes. This review paper mainly focuses on the research effort over designing the kernel functions for various objectives. Most of the strategies for image classification by SVM kernel have been analyzed for remotely sensed images. There is very interesting property of SVM and such kernel-based system has been studied that as soon as a specific kernel function has been chosen, it is feasible to practically work in any dimensional space without addition in cost of computation, as feature mapping was never found to be that effective task. In fact, knowing the type of feature to be mapping is also not mandatory. meter of the problem into a quadratic optimization technique. Hence, SVM is used to locate optimum boundaries between classes, which in return generalize to unseen samples with least error among all possible boundaries separating two classes. SVM uses density estimation function for developing easy and efficient learning parameters. Like other supervised algorithms, SVM also undergo into Training, Learning and Testing Phase for classifying any image. Besides all parameters, training sample selection and optimization is crucial part that affects the classification accuracy of remote sensing images [16]. The above survey revealed that machine learning performs best in classification of satellite images. They prefer can be done much better by evaluate texture contribution to perform better classify.

3. Methodology

Satellites orbiting the Earth provide a comprehensive view of the planet's surface, regardless of geographical boundaries or political borders. This global coverage allows for monitoring and analysis of remote or inaccessible areas, such as polar regions, dense forests, or disaster-stricken areas, where ground-based observations may be limited or impossible. We have proposed classification model with feature extraction and SVM classifier.

It is a kernel learning method for classification problems in which linear separation is not possible in the input space. SVM operates a non-linear transformation of the original input space X into a high dimensional feature space F, where optimal separating hyperplanes can be found. This is done by using a reproducing kernel function which plays a key role in the final performance of the classifier. In this paper, we consider the most general choice, the Gaussian kernel function. The kernel width associated to the Gaussian, σ, is adjusted by considering a nested 10-fold cross-validation process. The separating hyperplane is optimal when it maximizes the distance (margin) between the hyperplane and the closest points of the two classes (called support vectors), resulting in a good performance for the generalization set. Decision boundaries are smoothed to deal with the non-separable case by introducing slack-variables, relaxing the hardmargin constraint. A cost parameter defined by the user, C, balances pressure on margin maximization and pressure on errors. Again, we set this parameter by considering a nested cross-validation [17,18,19]. In Figure the proposed method for classification of Remote sensing images as shown

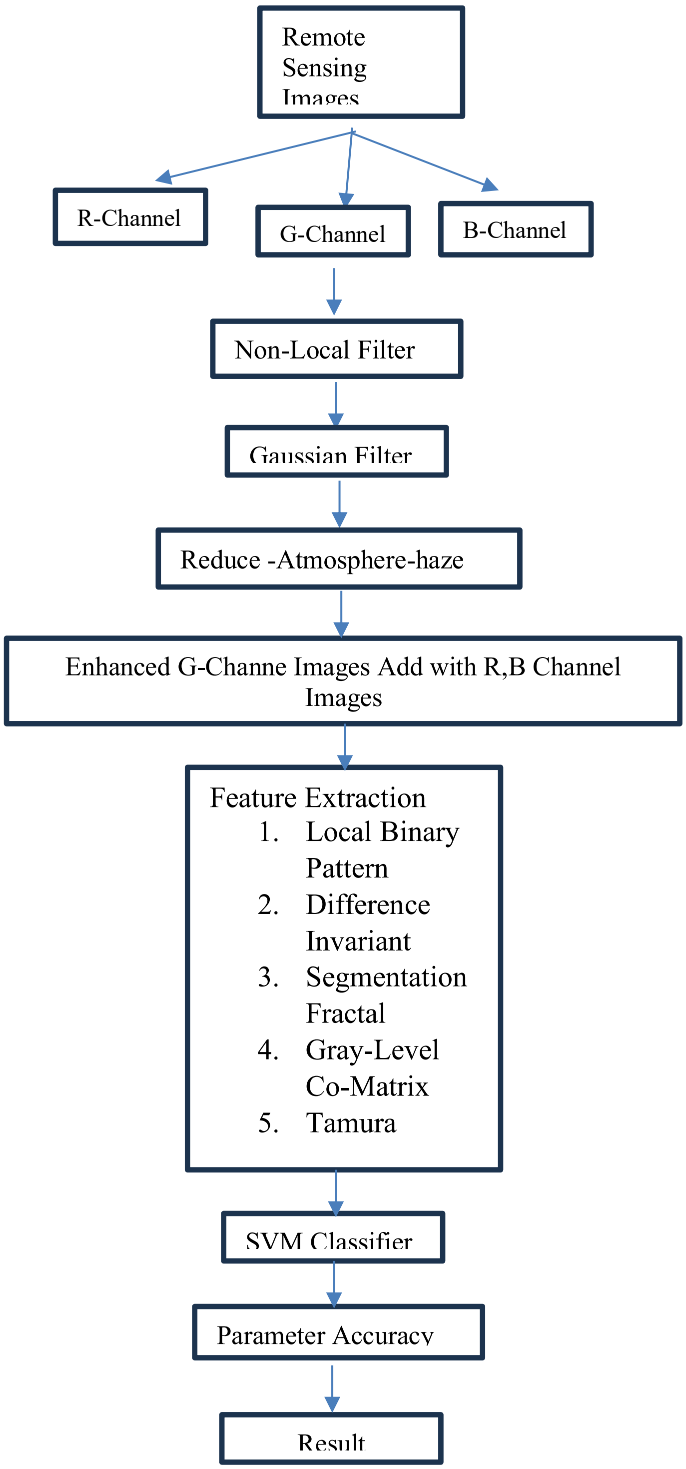

Figure 1 Classification Model of Enhanced Remote Sensing images

SVM classifier are considered the most uncertain, i.e., the ones for which f has the minimum value. This approach is usually referred to as marginal sampling (MS). In our approach, we consider that the position of the hyperplane could be not very precise, especially in the first iterations of the algorithm, where few labelled samples are used for training. MS with random selection: at the first iterations of the active learning process, random selection generally leads to accuracies that are higher than those obtained by MS-based technique. Thus, introducing different levels of randomness in the selection of the unlabeled samples can be beneficial, especially in the first iterations [20,21,22]. Implementation of SVM by the MATLAB uses the pairwise classification strategy for multiclass classification. SVM classification output is the decision values of each pixel for each class, which are used for probability estimates. SVM includes a penalty parameter that allows a certain degree of misclassification, which is particularly important for non-separable training sets. The penalty parameter controls the trade-off between allowing training errors and forcing rigid margins [23,24,25].

4. Datasets

The open remote scene picture dataset WHU-RS19 was obtained using Google satellite images. With 19 different scene types—including airport, bridge, airplane, and other scenes—it is a frequently used dataset for scene categorization and retrieval applications. The dimensions of every picture in the WHU-RS19 collection are 600 × 600 pixels in RGB color space.

Wuhan University has created a new aerial picture collection called AID using Google Earth photos. It has thirty different scene kinds, including baseball field, airport, and airplane. Every picture in AID is the same size in the RGB color space, 600 * 600 pixels, much like the WHU-RS19 dataset. There are 200–400 examples in each category, each measuring 600 by 600 pixels in RGB.

The project makes use of the UCMERCED land-use dataset. The national maps of the US Geological Survey were the source of the dataset extraction. 21 land-use classifications make up the dataset, which was obtained by hand-picking 100 photos for each class. The size of each picture is 256x256 pixels.

5. Result and Discussion

In this research work we are performing classification of Remote Sensing images using WHU-RS19, AID, UC-MERCED datasets. The proposed methods are compared with other method for accuracy. We have used Matlab2018a for this research work. The SVM classifier with quadratic nature is used with 10fold cross validation.

In Figure 2,3,4 Graph of Accuracy Comparison of WHU-RS19, UC-MERCED, AID datasets with their different methods are provided.

In Table 1,2,3 Accuracy comparison of WHU-RS19, UC-MERECED, AID datasets with their different methods are provided.

Table 1 Accuracy classification comparison of WHU-RS19 datasets with different methods

S.NO	OBJECTS	Purposed	BoVW [26]	SPM [26]	LDA [26]	LLC [26]	pLSA [26]
1	Airport	83.7	78.1	68.4	68.4	78.1	78.1
2	Beach	84.6	75.6	74.9	74.9	75.6	75.6
3	Bridge	85.9	85.6	26.9	26.9	85.6	85.6
4	Commercial	82.9	82.4	32.4	32.4	74.6	74.6
5	Desert	84.6	89.4	70.2	73.4	71.6	72.2
6	Farmland	86.9	75.6	38.5	38.2	75.6	75.6
7	FootballField	87.9	79.6	36.9	39.3	61.2	61.2
8	Forest	75.2	82.4	74.9	74.9	71.6	71.6
9	Meadow	79.3	74.5	48.5	48.3	74.5	46.8
10	Mountain	83.6	64.2	63.1	70.1	56.2	36.8
11	Park	86.8	71.5	64.9	60.9	71.5	71.5
12	Parking	80.1	71.2	58.6	58.6	71.2	71.2
13	Pond	85.7	74.5	48.9	48.9	74.5	52.7
14	Port	85.2	78.6	42.8	42.8	76.2	76.4
15	Railway -station	76.2	69.8	60.2	86.1	61.8	61.8
16	Residential	87.6	75.9	68.5	78.9	75.9	75.9
17	Rever	82.5	67.8	67.9	71.4	67.8	67.8
18	Viaduct	78.9	60.5	72.6	72.4	60.5	60.5
19	Accuracy %	82.3	75.52	56.6	59.2	70.1	67.5

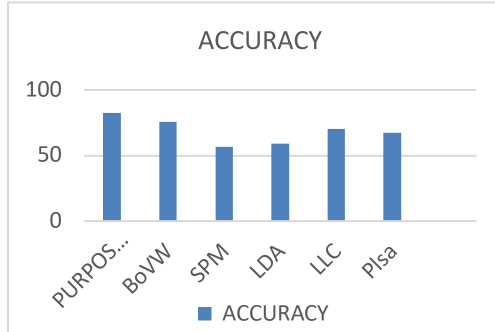

Figure 2 Graph of Accuracy comparison with different methods of WHU-RS19 datasets

Table 2 Accuracy classification comparison of UCMERCED datasets with different method

	OBJECTS	Proposed	LDA [26]	LLC [26]	pLSA [26]	SPM [26]	VLAD [26]
1	Agriculture	87.5	69.3	78.1	71.2	78.1	78.1
2	Airplane	81.2	62.5	75.6	74.5	74.9	75.6
3	Baseball-Diamond	74.6	72.5	66.9	69.8	32.4	66.9
4	Beach	83.7	46.8	73.6	75.9	72.4	73.6
5	Building	81.6	68.6	75.6	67.8	38.5	75.6
6	Chaparral	75.6	75.5	74.5	58.9	36.9	74.5
7	Dense Residential	78.9	46.3	76.9	72.3	76.9	76.9
8	Forest	89.1	70.2	74.5	76.8	48.5	74.5
9	Freeway	89.9	55.6	64.2	73.4	63.1	64.2
10	Golf Course	79.2	62.3	88.6	78.1	64.9	77.9
11	Harbor	76.5	55.2	71.2	74.9	62.6	71.2
12	Intersection	83.7	78.6	74.5	85.6	49.6	74.5
13	Medium-Residential	86.3	68.3	63.4	66.9	39.7	63.4
14	Mobile Home Park	78.6	66.9	69.8	73.6	58.9	69.8
15	Over Pass	83.4	59.7	75.9	75.6	75.9	68.7
16	Parking Lot	77.8	60.3	67.8	74.5	67.8	67.8
17	Rever	85.4	56.8	54.8	76.9	58.9	54.8
18	Runway	80.6	62.1	72.3	78.6	49.7	72.3
19	Spare Residential	83.8	67.4	76.8	64.2	76.8	76.8
20	Storage Tanks	81.7	69.3	73.4	68.9	46.8	73.4
21	Tennis Court	87.5	62.5	78.1	78.1	78.1	78.1
22	Accuracy	82%	64.12	73	72.88	57.17	72.48

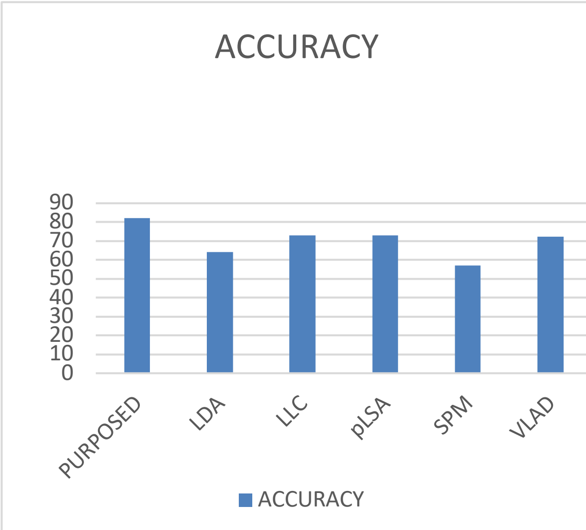

Figure 3 Graph of Accuracy comparison with different methods of UC-MERCED datasets

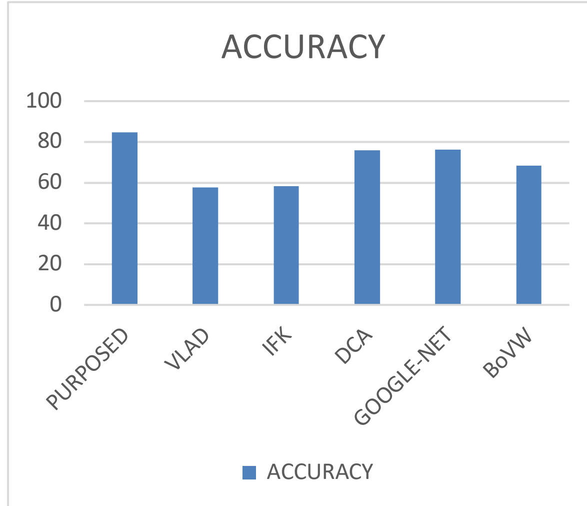

Figure 4 Graph of Accuracy comparison with different methods of AID datasets

Table 3 Accuracy classification comparison of AID datasets with different method

S.NO	OBJECTS	Proposed	VLAD [27]	IFK [27]	DCA [27]	GOOGLE-NET [27]	BoVW [27]
1	Airport	78.9	41.08	45.43	69.35	71.60	67.8
2	Bareland	86.9	60.65	65.84	82.47	81.18	48.6
3	Baseball field	75.1	35.86	42.32	75.35	78.64	58.7
4	Beach	84.9	55.50	64.83	91.28	88.28	82.6
5	Bridge	81.6	33.83	50.77	77.25	80.12	78.2
6	Centre	96.8	23.38	34.74	50.60	52.86	77.6
7	Church	88.4	48.80	59.58	65.51	67.64	65.8
8	Commercial	85.5	64.29	63.46	63.52	58.00	48.6
9	Dense Residential	85.9	67.29	59.59	83.09	84.15	65.4
10	Desert	84.2	50.48	63.19	87.07	86.44	66.2
11	Farmland	82.7	36.37	52.58	88.41	89.58	73.9
12	Forest	87.8	79.91	79.69	87.69	87.29	77.1
13	Industrial	78.6	49.17	49.03	69.23	69.23	72.6
14	Meadow	89.2	65.04	70.87	87.38	89.29	74.1
15	Accuracy	84.7%	58.56	58.17	75.98	76.22	68.37

Classification accuracy highest in AID datasets 84.7 % in table 3 as compared to other methods and WHU-RS19 datasets all over accuracy 82.3 % and UCMERCED 82 %.

6. Conclusion

This article has Different feature used like linear binary pattern, gray level co- occurrence matrix, Tamura. AID, WHURS-19, UCMERCED datasets are enhanced using enhancement techniques images sets. This research only base on all over accuracy using machine learning. All three datasets all over accuracy above 80% like WHU-RS 19 (82.3 %), UCMERCED (82 %) and AID (84.7 %) higher than various methods. Hybrid model have been applied to several knowledge areas (e.g. medicine, biology, agriculture, security, and remote sensing) due to the excellent classification accuracy results. For classification Quadratic SVM classifier is used to perform feature based efficient based classification. To proposed method is observed to be better than other methods.

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