Satellite Image Classification using Machine Learning Technique

Dr. Khushbu R. Joshi
LDRP Institute of Technology and Research, Gandhinagar, India

Abstract— Satellites are used to monitor the earth's surface. During the day millions of images are taken by satellites. To analyze a large amount of data manually is a tedious task. An automatic classification technique is required that classifies the images into different classes. Machine learning techniques are extensively used for the classification of satellite images. In this study, we proposed a classification system that classifies the satellite images with high accuracy. In this paper, the features were extracted from the satellite images using the Higher-order Local Auto Correlation method. The EuroSAT dataset was used to train and test the model. The performance of the proposed system was evaluated by accuracy and F1-score. The experimental results showed good and remarkable results. Further, the results were improved by using different SVM kernels.

Key words: Image Classification, HLAC, Object Detection, Remote Sensing, Satellite Image, SVM

I. INTRODUCTION

The satellites are used for earth monitoring take a large number of images every day. The classification of the images is a difficult task. Here we require some automatic classification techniques that detect the features from the image and then classify the images automatically from a large amount of available data. SVM is a promising machine learning technology that classifies satellite images accurately.

Anita Dixit et al. [1] present a classification system for vegetation, soil, and water bodies. The SVM classifier was trained using Gray Level Co-occurrence Matrix and lifting wavelet features. The SVM performance was compared with k-nearest neighbor (kNN) and Relevance Vector Machine (RVM). The experiment results showed that the accuracy, sensitivity, and specificity of the SVM proved better. Phan Thanh Noi and Martin Kappas [2] compared three machine learning algorithms, kNN, Random forest, and SVM, for land cover classification using sentinel-2 imagery. The overall accuracy was achieved in the range of 90% to 95%. The higher overall accuracy achieved by SVM was around 93.76% to 93.96%, higher than kNN and Random Forest. Jozdani et al. [3] experimented to compare several deep learning and machine learning model architectures for urban mapping. All the classifiers are tested on two remote sensing images. The multilayer perceptron and SVM achieved the highest classification results. Przemysław Kupidura [4] presented a comparison of several texture analysis methods like gray level co-occurrence matrix, Laplace filters, and granulometric analysis for land use/land cover classification of Sentinel 2 satellite images. The highest result was achieved by granulometric analysis. In this paper, HLAC features are used to find the change detection from multi-temporal remote sensing data.

The paper is organized as follows. Section 2 describes the feature extraction technique. Section 3 gives an introduction to the dataset that we have used in this paper for the experiment. Section 4 contains a brief introduction of the SVM classifier and different kernels. Section 5 shows the final experiment performed on the dataset. The results and discussion are mentioned in section 6. Finally, section 7 shows the conclusion and future work.

II. FEATURE EXTRACTION

To classify the satellite images image features must be extracted from the given images. The satellite images are more texture-like images, in this paper, we have used the HLAC features to extract the features from the image dataset.

The HLAC was proposed by Otsu and Kurita in 1988. [5] The HLAC outperformed in various applications such as object detection [6], texture image classification [7], and gesture recognition [8]. The nth-order autocorrelation function can be characterized as

$$X(d_1, d_2, ..., d_N) = \int f(p) + f(p+d_1) + ... + f(p+d_N) \tag{1}$$

where f(p) shows the intensity of the reference pixel at point p and d1,d2. . .dN are N displacements.

The HLAC features are computed by applying the HLAC mask patterns to an entire image. Then the product of the mask and pixels are computed. All the products are then summed up to get the value of one feature.

Fig.1 shows the HLAC mask patterns for 3x3 mask size. In each mask, the black represents the “required” or reference points where the white color represents “not required” points. The HLAC features can be extended either by increasing order [9] or by increasing neighborhood distance [10]. The size of the local neighborhood is given by (2m+1)x(2m+1), where m is displacement distance. Fig.2 shows the HLAC mask patterns by increasing the neighborhood distance for the mask size 3x3, 5x5, and 7x7.

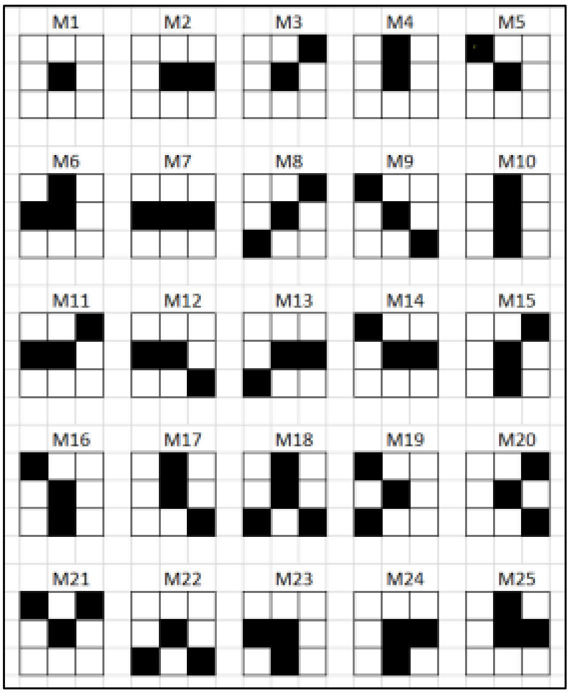

Fig. 1: HLAC mask patterns for 3x3 mask size

III. DATASET

To increase the performance of the supervised learning classification techniques, the dataset must contain high-quality images with an adequate number of classes. In this paper for the classification of Sentinel-2 satellite images, we have used an openly available dataset named, EuroSAT dataset, proposed by Helber et al. [11]. The dataset was proposed for the land use and land cover classification task. The dataset contains a total of 27,000 images with 10 different classes. Each class contains approximately 3000 images. The classification accuracy of different training-testing splits was evaluated by different machine learning techniques. To evaluate the performance of handcrafted features SIFT features were combined with BoVW (Bags of Words) and SVM. For different k-means clustering (k= 10, 100, 500) the performance was calculated.

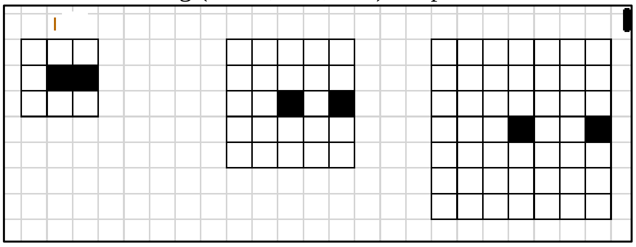

Fig. 2: HLAC mask patterns for different mask size

IV. CLASSIFIER

Support Vector Machine (SVM) is one of the most popular supervised binary classification algorithms since 1963. In 1995, Cortes and Vapnik [12] proposed support vector networks for two-group classification problems. SVM is used in many real-world problems such as text and image classification,1oil tank detection [13], and medicine analysis [14]. SVM provides kernel functions that separate the non-separable data into a higher-dimensional space. The widely used kernel functions are linear, polynomial, Radial Basis Function (RBF), and sigmoid kernel.

The linear kernel linearly separates the data according to their class. The restrictions of linear hyperplanes are their limited adaptability to different shapes.

$$K(Xi, Xj) = (Xi * Xj) \tag{2}$$

The polynomial kernel separates the data to a high dimension according to the polynomial degree, d.

$$K(Xi, Xj) = (1 + Xi * Xj)^{d}) \tag{3}$$

The RBF kernel is also known as radial basis function or Gaussian kernel. When SVM is trained with the RBF kernel, two parameters C and gamma must be considered. The parameter C is a regularization parameter which remains common for all SVM kernels. It defines the trade-off between margin maximization and error minimization.

$$K(Xi, Xj) = \exp(-\gamma \|Xi * Xj\|^{2}) \tag{4}$$

The gamma parameter could be perceived as the inverse of the radius of samples influence. and the Sigmoid kernel function is given by

$$K(Xi, Xj) = \tanh(ax^{T}y + c) \quad (5)$$

For the SVM performance, proper choice of C and gamma is essential. The good values of C and gamma can be selected by grid search algorithm.

V. EXPERIMENT

The experiment has been carried out in two phases. For the first experiment, We have taken here only 2 classes only of the EuroSAT dataset i.e. residential and sealake images. Each class contained3000 labeled images. The features are extracted from the images using HLAC. Different mask sizes like 3x3, 5x5, and 7x7 have been taken for the experiments to check the accuracy. For the 3x3mask size, different kernel functions are applied. To evaluate the classifier performance Accuracy and F1-score have been used. Also, to make the features invariant to scale change, different mask size features were combined to form multi-dimensional features. In the second experiment, we have used the full dataset, i.e. 10 classes. So, first, we will find the HLAC features for all 10 classes, a total of 27,000 images. Then the SVM classifier is used as a multi-class classifier. To classify the multi-class, the one-vs-all method is used. The different kernels like linear, polynomial, and RBF kernel are used for evaluation. The best kernel parameters can be found by using a grid search algorithm. SVM classifiers are trained using 5 fold cross-validation.

VI. RESULTS AND DISCUSSION

Table 1 shows the classification accuracy and F1-score of the two classes for different kernels. Here for the different mask sizes like 3x3, 5x5, and 7x7. The F1-score of the linear kernel was higher for different mask sizes. In the multi-dimensional, different mask size patterns, i.e., 3x3,5x5 and 7x7, were combined. The F1-score for polynomial kernel was noted higher i.e. 0.91.

Mask size	Order	F1-score		
		Linear	Polynomialal	RBF
3x3	2	0.9382	0.9208	0.9158
5x5	2	0.9491	0.9344	0.9065
7x7	2	0.94	0.91	0.8692
Multi-dimensional	2	0.90	0.912	0.89

Table 1: Performance Evaluation of HLAC Features For Different Kernel Parameters

Table 2 displays the EuroSAT dataset's overall classification accuracy for 10 classes. The results were compared to the benchmarks outlined in [11]. In the benchmark, the maximum classification accuracy with SVM was 70.05% with a train and test splitting ratio of 80/20 employing the SIFT (BoVW) approach.

Whereas in the proposed method, the SVM classifier was able to effectively distinguish between distinct classes, improving accuracy to 89.35% with a train and test splitting ratio of 80/20 using HLAC feature extraction. Different kernel methods, such as linear kernel, polynomial kernel, and RBF kernel, were used to increase accuracy. The accuracy for RBF kernel was minimum i.e., 87.84%, for linear kernel was intermediate i.e., 88.25% and for polynomial kernel was highest i.e., 89.35%. The F1-score was minimum for the RBF kernel was 85.37 and maximum for 86.26 using a polynomial kernel.

Classifier	Method	Accuracy (%)		
SVM (Benchmark)	SIFT (BoVW)	58.55 (k=10)	67.22 (k=100)	70.05 (k=500)
SVM (our result)	HLAC (3x3, 25 masks)	87.90 (RBF kernel)	88.25 (linear Kernel)	89.35 (Polynomial kernel)

Table 2: Comparison of Classification Accuracy (%) Of HLAC Features with Benchmark Results

VII. CONCLUSION AND FUTURE WORK

In this paper, we have compared two feature extraction techniques SIFT (BoVW) and HLAC with SVM classifier. The result showed that SVM provides good classification accuracy using HLAC feature extraction methods when compared with benchmark SIFT (BoVW) method. Further, results can be improved by changing kernel parameters.

Here, we can able to achieve maximum accuracy of 89.35% using a polynomial kernel for 10 classes. The order of the HLAC features can be extended to higher-order to improve the results. Also, different machine learning and deep learning techniques like ResNet models can be used to improve the result.

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