

High-Resolution Remote Sensing Satellite Images Classification and Retrieval Model based on Gray Level Co-Occurrence Matrix

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Abstract - Natural disasters, deforestation and desertification, forest fires, illicit tree felling for agriculture, urban expansion, and climate change monitoring are all aided by remote sensing satellite images. The volume of image datasets is evolving exponentially as remote-sensing technology advances and the number of Earth observation satellites rises. Machine learning algorithms are capable of quickly and efficiently classifying and retrieving images. Image pattern identification and classification process are done by different Machine learning algorithms from an image search engine that is given by input query images. The Naïve Bayes, SVM Linear, Decision tree, and Random Forest algorithms accuracy are evaluated here. The capability of making effective classification and quick predictions are supported by Naive Bayes Classifier with rapid machine learning models. Both SVM linear and non-linear algorithm achieves high accuracy while utilizing less computational power. The decision tree is the most powerful and widely used algorithm for image categorization and prediction. To improve the dataset's forecast accuracy, Random Forest aggregates the outcomes of numerous decision trees applied to different subsets of the dataset. This study proves that the accuracy of Naive Bayes Classifier is 60%, SVM of 61%, Decision Tree 62%, and Random Forest 65% when using the UC Merced dataset.

Index Terms-Image retrieval, Satellite Images, SVM, Decision Tree, Random Forest.

I. Introduction

Remote sensing satellite image classification and predicting the best one by using the retrieval methods are challengeable tasks now. With the advancement and improvement of satellite image sensors, the resolution of images captured has improved due to advanced image processing techniques with greater high-resolution pixels. While satellite images are not always high resolution, comparing them is more difficult, clouds blocking the view is another distortion, and double-checking for ground-truthing wastes a lot of time. Satellite images are commonly used for natural resource management, scheme planning, monitoring, and forecasting, among other things for the field of agriculture, harbor, seashore, and transportations. The Gray-Level Co-Occurrence Matrix

is one of the feature extraction methods which is implemented by supervised algorithms. The preprocess analysis completes with efficient classifications algorithms is examined with current image datasets. The classification method produces superior results while retrieving remote sensor satellite photos in a short period and with high precision. The image categorization results in higher dimensions are a significant advantage of the machine-learning approach. The importance of comparing and assessing image retrieval methods utilizing three classification algorithms to categorize image pattern recognition is giving better results. Many academics have created classifiers of Random Forest, Decision Tree, Naive Bayes, Support Vector Machine, K-Nearest Neighbor. In this paper, we will be comparing four different classification methods. Experiments conducted on the land cover satellite images dataset with different classification algorithms, then we will elucidate according to the classification performances to choose the best retrieval methods for remote sensing images.

II. Related Work

According to Park, Dong-Chul [1] realize the image classification using the Naïve Bayes classifier gives accurate classification results with minimal training time when compared to conventional supervised or unsupervised learning algorithms. The classifier gives the greatest a posteriori decision rule for both training time and classification accuracy from Caltech image data sets. The proposed work used a Discrete cosine transform (DCT) tool for converting images into their frequency components for image compression. The classifier proved accuracy is 77.2% and less training time of 0.42 seconds while comparing with Centroid Neural Network, Fuzzy C-Mean, and Multi-Layer Perception Neural Network [1].

Ansari, Mohd Aquib [2], springs an effective approach to image retrieval using SVM classifier uses content-based image retrieval with query image with greater system performances. The work is done by the dual steps followed by extracts color by color and edge directivity descriptor (CEDD) and texture by using two-level discrete wavelet transform (2D-DWT) of color, shape, texture descriptors. Finally, SVM Classifier classifies the images into different classes for handling irrelevant images by the usage of Euclidean distance for similarity measurements. For Wang, Caltech, and Corel image databases, this proposed approach achieved an average accuracy of 85%, 90 %, and 78 %, respectively in terms of precision, recall [2].

M K Ghose, Ratika Pradhan, and Sucheta Sushan Ghose [3], evidencing remotely sensed satellite data with decision tree classification by using Spectral Separability Matrix. The spectral distance is calculated by the difference of minimal and maximal spectral value for the specific band while the tree is built by the Top-down method. The accuracy compared with Decision tree with Maximum Likelihood Classifier (MLC) and proves the better results of 98%. The proposed work considered Turbid water, Clearwater, Upland Fallow, River, wetland, and drainage is considered with assessing the accuracy with confusion matrix since the multi-spectral IRS-1C/LISS III image used as a model. The training set is considered is the best part for producing high accuracy for testing data. Thus, again decision tree proves its flexibility and simplicity, and computational efficiency [3].

Bhosle, Nilesh & Kokare, Manesh [4], convey in found of the classification-based on Random Forest approach is seen as a developing way to overcome the semantic gap, it takes an input vector and categorizing according to each tree in the forest, finally, the majority of votes are used to conclude the input vector class. Experimental evaluation is done by two different data set of Corel and Caltech datasets. Imbalanced training set problem is overcome by dynamic learning approach. [4].

III. Methodology

In this paper, to examine the performance of several classification algorithms on a variety of data training sample strategies, an area of 256 x 256 pixels of Landcover to examine the performance of several classification algorithms on a variety of data training sample schemes of ten classifications areas.

3.1. Image Data Set

Dataset has been collected from the data sources of various metropolitan regions around the country, massive imagery of Geological Survey's Imagery collections from the United States with 10 categories (USGS).

National Map Urban Area Imagery collection with 256X256 of each pixel size.	Name of the Category	No. of Images
	Agriculture	100
	Aircraft	100
	Baseball Diamond	100
	Buildings	100
	Chaparral	100
	Harbor	100
	Intersection	100
	Parking Lot	100
	Storage Tanks	100
	Beach	100
	Transportation	100

Table 1. Imagery collection of Urban Area

Table 1. shows the UC-Merced Landuse dataset with ten categories each 100 images with 256X256

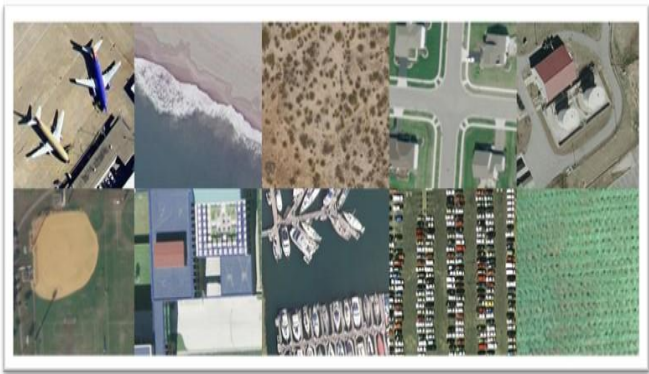


Figure 1. Sample Land use Satellite images from the Dataset

Figure1.illustrated with various metropolitan regions around the country, the images were manually extracted from massive imagery collections. In Land, the cover area is divided

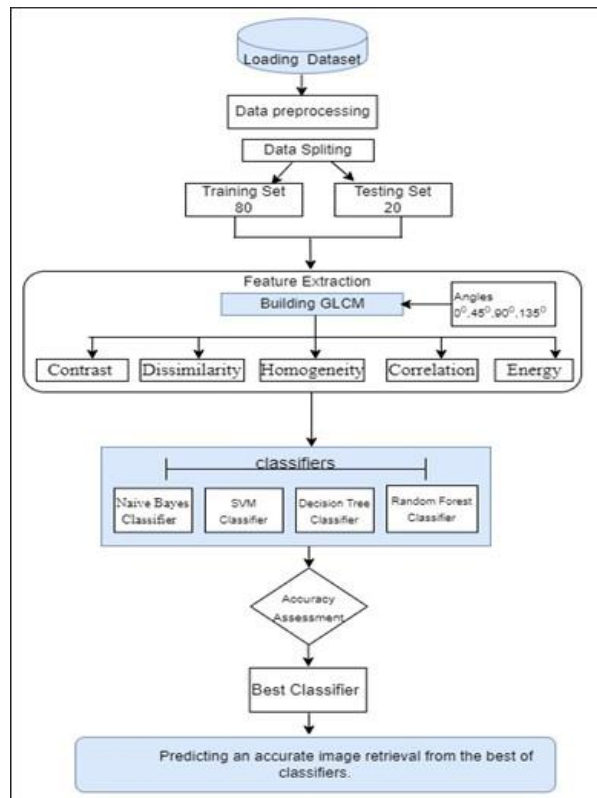
into 10 categories: agriculture, aircraft, baseball diamond, seashore, buildings, and transportation, chaparral, harbor, intersection, parking lot, storage tanks of each class taken 100 images.

3.2. General Flow of different Classifiers

Figure 2. Shows the image classifications and retrieval based on gray level co-occurrences matrix with different machine learning algorithm classifiers. The process is illustrated by the following steps.

Step1. Loading 1K dataset of satellite images with 10 classes of land use area.

Step2. The pixel value of each image is 256 x 256 as actual data, which is converted to 128 x 128- Pixel resolution in a preprocessing session.



for giving an accuracy of good results. Deriving the best classifier which leads to giving good prediction results in image retrieval.

Figure 2. Classification and Retrieval based on GLCM with classifiers

Step3. Dataset is divided by two splits, one as training samples and the other is testing samples with the ratio of 80:20.

Step4. Feature extraction approaches of Gray Level Co-occurrences Matrix are calculated.

Step5. A principal component analysis is assessed for Image dimension Reduction.

Step6. Different classifier approaches are applied to image collections with Decision Tree, Naïve- Bayes, Random Forest and SVM

Step7. Accuracy assessment with confusion matrix for each specified classifier with its Reliability is monitored.

Step8. Compares different classifiers since that choosing the best classifier for image retrieval.

Step9. Finding accuracy for each different classifier has to predict the good accuracy for image retrieval.

The training samples of each 10 class have 800 images whereas testing samples of each class have 200 images. Training samples are trained as a model

IV. Classification Techniques Of Remote Sensor Satellite Images

4.1. Naïve-Bayes Classifier

Naive Bayes classifier straightforwardly classifies remote sensor image datasets and performs computations quickly. For training samples, it verifies the number of features linearly way. It processes binary and multi-class classification and provides accurate predictions as a result while based on their attributes. This classifier assigns a class to a set of features based on conditional probability. The training set refers to the learning process, whereas the test set refers to the process of the testing set for more proper classification.

4.2. SVM Classifier

The classification of data with dissimilar groups in multidimensional space gives a hyperplane that results in good classification for training data. Generation of selecting hyperplane with a good one, that reduces an error, and to find maximum marginal hyperplane. The closest to the hyperplane are support vectors which play a crucial role in the classifier. The distance between the two lines on the class points that are closest to each other is known as a margin. This method works well with linear separable classes and not with complex data.

4.3. Decision Tree Classifier

The classifier is preferably the best suite for classification rather than regressions. The classifier is tree structure graphical representation gives best possible solution for a problem which denotes parent expands to

leaf according to the choice of decision. Tree expansion is based on making questions to the problem which derives from a decision based on the term of yes or no. The classifier is preferably on categorical data and numeric data. Attribute selection measures the best attribute of a given problem derives its node to leaf one which is assessed by information gain and Gini index. The impurity of a given node is identified by calculating entropy and removing an unnecessary node by pruning.

4.4. Random Forest Classifier

Random forest is more versatile classification and simpler to use than other supervised learning algorithms. Data samples chosen by randomly for building decision tree that receives the prediction from each subtree and votes for optimal one. A forest is a group of decision tree classifiers that are technically based on the divide and conquer approach of decision trees on a randomly split dataset. The attributes of each decision tree are formed using an attribute selection indicator such as gain, gain ratio, or Gini index.

V. Feature Extraction Method

Feature extraction helps to increase training speed by removing the redundant data for making the dimensionality reduction. The raw data is divided and reduced without affecting and losing any important or relevant information from the pixel matrix. By selecting a compact feature vector with variable combinations from pixels increases the accuracy. Identify the key feature from the original data set to derive a new one by selecting or combining variables. This paper focuses on the grey level co-occurrences matrix for the real data set with good retrieval results.

5.1. Gray Level Co-occurrences Matrix

Colour, Texture, shape, positions, and histogram are the feature extraction methods of image retrieval. An image intensity and spatial pixel values are authenticated by colour feature while another feature of the histogram is characterized by one-dimensional values not speculated for all time. But GLCM is manipulated by a two-dimensional matrix for the chance of frequency of occurrence in texture analysis with good prediction meanwhile GLCM is termed as a second-order statistical feature that is used for the degree of correlation between the pair of pixels. The distance is denoted by the use of pair of pixels; orientation denotes the angle of the pixel with $N \times N$ number of gray values. GLCM is proposed by two parameters of Greycomatrix for finding the co-occurrences matrix, Greycoprops for texture properties of a GLCM.

Step1. Read image with grayscale with (128 x 128) pixel sizes as quantization.

Step2. Calculate greycomatrix of an image.

Step 2.1. Make square Matrix with $N \times N$ size, N is number of gray levels.

Step 2.2. Make Window size W for sample S .

Step 2.3. Calculate spatial relationship with intensities of i, j , with the sum of all elements denotes spatial relationship.

Step 2.4. Make GLCM symmetric as transposed copy, add to GLCM then Normalize as $P_{i,j}$.

Step 2.5. Calculate the selected GLCM Feature.

Step3. Compute GLCM Properties as.

Step3.1. Contrast $\sum_{i,j=0}^{levels-1} P_{i,j}(i-j)^2$

Step3.2. Dissimilarity $\sum_{i,j=0}^{levels-1} P_{i,j}|i-j|$

Step3.3. Homogeneity $\sum_{i,j=0}^{levels-1} \frac{P_{ij}}{1+(i-j)^2}$

Step3.4. Energy $\sum_{i,j=0}^{levels-1} P_{i,j}^2$

Step3.5. Correlation $\sum_{i,j=0}^{levels-1} P_{i,j} \left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} \right]$ μ as the GLCM mean, σ^2 as variance of intensities

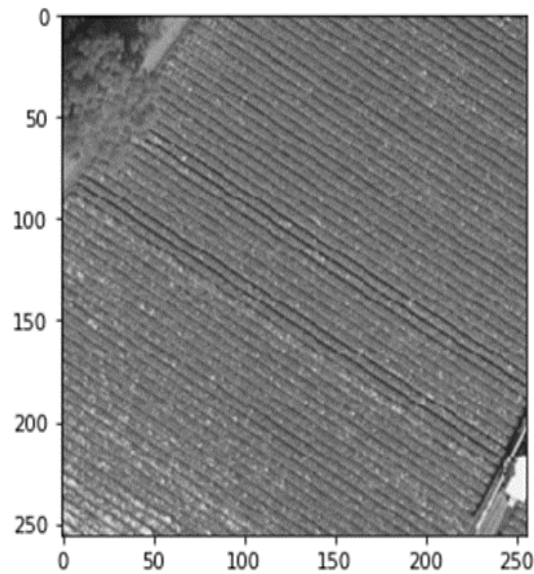


Figure 3.a. Agricultural Image

contrast	[256.92670037 272.975594 435.08564645 713.16236832]
dissimilarity	[11.99578738 12.28189158 16.11894914 20.72684352]
homogeneity	[0.09237682 0.08407756 0.06632639 0.05122305]
energy	[0.01959749 0.01893232 0.01803265 0.01727287]
correlation	[0.73336746 0.7153306 0.55021128 0.2562005]

Figure 3.b. GLCM of an Agricultural image

Figure 3. an illustrated for a sample agricultural image with its grayscale representation, figure 3.b. tabulate GLCM feature for a sample image, contrast measures intensity of pixel with its neighboring pixel, correlation measures relate to the neighboring pixel, energy returns the sum of the square of all elements, homogeneity as closeness distribution of GLCM diagonal range [0,1].

Vi. Results And Discussion

All assessments were supported by Windows ten computer with an Intel(R) Core (TM) i5 1.6 GHz processor, 8 GB RAM, 1 TB HDD, For the experiment in the Machine Learning with Python Environment.

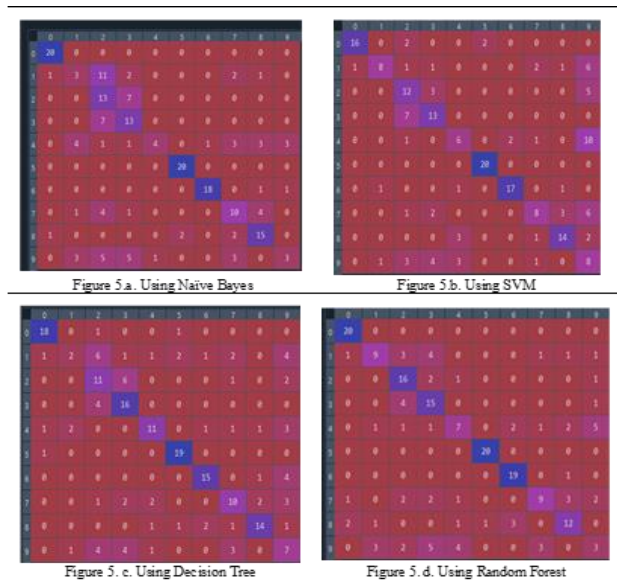


Figure4. Confusion Matrix for different Classifiers

Figure 4. Illustration of result assessment with confusion matrix each classifier of ten classes category image dataset. The percentage of best classification of an image is represented by the greater number of blue diagonal values. Here random forest and decision tree give good accurate assessment representation for an image, between actual and predicted values.

Categories	Precision	Recall	F1-score	Support
agricultural	0.91	1.00	0.95	20
airplane	0.27	0.15	0.19	20
baseball diamond	0.32	0.65	0.43	20
beach	0.45	0.65	0.53	20
buildings	0.80	0.20	0.32	20
chaparral	0.91	1.00	0.95	20
harbor	0.95	0.90	0.92	20
intersection	0.50	0.50	0.50	20
parking lot	0.62	0.75	0.68	20
storage tanks	0.43	0.15	0.22	20
Accuracy	-	-	0.60	200
Macro avg	0.62	0.59	0.59	200
Weighted Avg	0.62	0.59	0.59	200

Table 2. Accuracy of Naïve Bayes

Categories	Precision	Recall	F1-score	Support
agricultural	0.94	0.80	0.86	20
airplane	0.80	0.40	0.53	20
baseball diamond	0.44	0.60	0.51	20
beach	0.57	0.65	0.60	20
buildings	0.46	0.30	0.36	20
chaparral	0.91	1.00	0.95	20
harbor	0.89	0.85	0.87	20
intersection	0.62	0.40	0.48	20
parking lot	0.74	0.70	0.72	20
storage tanks	0.22	0.40	0.28	20
Accuracy	-	-	0.61	200
Macro avg	0.66	0.61	0.62	200
Weighted Avg	0.66	0.61	0.62	200

Table 3. Accuracy of SVM

Categories	Precision	Recall	F1-score	Support
agricultural	0.86	0.90	0.88	20
airplane	0.40	0.10	0.16	20
baseball diamond	0.41	0.55	0.47	20
beach	0.55	0.80	0.65	20
buildings	0.69	0.55	0.61	20
chaparral	0.83	0.95	0.88	20
harbor	0.79	0.75	0.77	20
intersection	0.56	0.50	0.53	20
parking lot	0.78	0.70	0.74	20
storage tanks	0.29	0.35	0.32	20
Accuracy	-	-	0.62	200
Macro avg	0.61	0.61	0.60	200
Weighted Avg	0.61	0.61	0.60	200

Table 4. Accuracy of Decision Tree

Categories	Precision	Recall	F1-score	Support
agricultural	0.83	1.00	0.91	20
airplane	0.64	0.45	0.53	20
baseball diamond	0.57	0.80	0.67	20
beach	0.52	0.75	0.61	20
buildings	0.50	0.35	0.41	20
chaparral	0.95	1.00	0.98	20
harbor	0.79	0.95	0.86	20
intersection	0.64	0.45	0.53	20
parking lot	0.63	0.60	0.62	20
storage tanks	0.23	0.15	0.18	20
Accuracy	-	-	0.65	200
Macro avg	0.63	0.65	0.63	200
Weighted Avg	0.63	0.65	0.63	200

Table 5. Accuracy of Random Forest

Table 2. to Table 5. shows the accuracy of different classifiers are assessed and compared for the test dataset by measuring their metrics of precision, recall, and f1 score values.

Table 6. Overall accuracy for different classifiers

Overall Accuracy			
Naïve Bayes	SVM	Decision Tree	Random Forest
60%	61%	62%	65%

Table 6. illustrated the overall accuracy for each classifier with 1K image dataset. The Accuracy Naïve-Bayes classifier is 60%, the SVM classifier for 61%, the Decision tree Classifier is 62%, finally, Random Forest classifier is 65% as prescribed as experimental values.

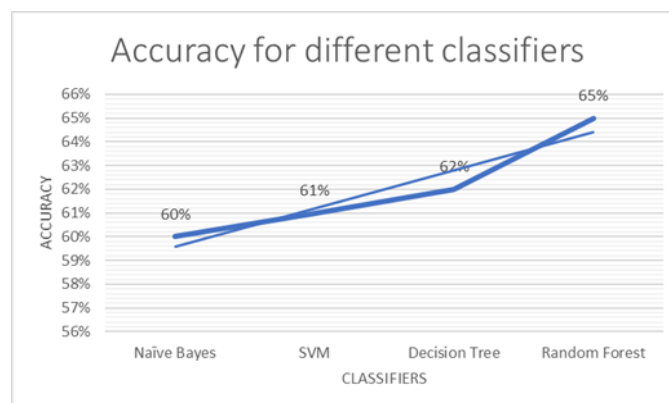


Figure 5. Accuracy comparison chart with different classifiers

Figure 6. Illustrated accuracy comparisons of Naïve-Bayes, SVM, Decision tree and random forest, whereas random forest proves the highest percentage 65%, the next to it SVM is 62%.

Vii. Conclusion

In this paper, Naïve Bayes, SVM, Decision tree, and Random Forest classifiers are evaluated with remote sensor satellite image datasets to get good retrieval performances. The main aspiration of this research is an assessment of the classifier with its accuracy to provide a comparative result that helps to enhance future research work. The random forest 65 %and decision tree 62% prove good accuracy with another classifier. Developing the best classifier, which leads to good image retrieval prediction outcomes. The enhance of future work for image retrieval with good prediction results through Transfer Learning methodology for a lakh of images with highest accuracy rate.

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