# Satellite Images Scene Classification Based Support Vector Machines and K-Nearest Neighbor

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## Abstract

Satellite image classification is a valuable technique for producing worthy information. This paper deal with high-resolution satellite for scene classification. In this research presents three algorithms were used to extract the features which are local binary patterns, gray level co-occurrence matrix, and color histogram features. The classification process included the use of two types of data mining techniques belongs to supervisor classification which are support vector machines, and k-nearest neighbor. Test results explain that the proposed classification method obtains a very auspicious performance.

**Keywords:** Supervised Classification, Satellite Images, Feature Extraction, GLCM, LBP, SVM, KNN.

# تصنيف مشهد القمر الصناعي باعتماد خوارزمية شعاع الدعم الالي وخوارزمية الجار الأقرب

**غيداء وليد ناجي و جمال مصطفى التويجري**

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## الخلاصة

تعتبر تقنية تصنيف صور الأقمار الصناعية من التقنيات المهمة والمفيدة لتوليد معلومات قيمة في مجالات الاستشعار عن بعد. في هذه الورقة البحثية سيتم تصنيف مشاهد لأقمار صناعية عالية الدقة للمناطق مختلفة. تم استخدام ثلاث خوارزميات لاستخراج ميزات الصورة وتم اعتماد الميزات التي تم استخراجها من الخوارزميات الثلاث. في مرحلة التصنيف تم اعتماد

تقنيتين من تقنيات التنقيب عن البيانات، عملية التصنيف تتضمن على استخدام خوارزميتين من خوارزميات التصنيف الخاضع للأشراف وهي خوارزمية شعاع الدعم الالي وخوارزمية الجار الأقرب حيث بينت النتائج على ان خوارزمية شعاع الدعم الالي كانت الأفضل وبنتائج جيدة جدا مقارنة مع خوارزمية الجار الأقرب.

**الكلمات المفتاحية:** التصنيف الخاضع للأشراف، صور الأقمار الاصطناعية، استخراج الميزات، مصفوفة التواجد للمستويات الرمادي، خوارزمية الأنماط الثنائية المحلية، خوارزمية الشعاع الدعم الالي، خوارزمية الجار الاقرب.

## Introduction

Satellite images play an important role in giving the geographic information needed for different purposes. Satellite and remote sensing technologies gather images at uniform intervals. The technology is growing rapidly and the amount of data is growing at a great rate where the amount of data received at data centers is massive and growing exponentially. To extract useful information and interpret it from large quantities of satellite images, we need powerful and sophisticated mechanisms. Classification of satellite image considers a robust mechanism to extract data from a massive amount of satellite images. The classification of satellite images includes the compilation of pixels into importance classes. The process of classifying satellite images requires from analyst to make a lot of decisions and choices, which makes the classification of satellite images somewhat complex [1]. A lot of geographic information is present in remote sensing images. Geographic information can be important in many areas such as business, science, research, and governments, it can also be used in city planning and natural resource analysis in certain areas [2].

### Related Work

Various techniques are proposed for the classification of satellite images in this section provides a set of previous techniques that dealt with the classification of satellite images:

**Manali Jain, Amit Sinha [3]:** Introduce a way to classify satellite images through Gabor Filter using SVM. The focus of this work was on five class of satellite images which is desert, forests, mountains, residential areas and agriculture. A collection of features was used in this research which is a feature of color, texture, and shape. These features were extracted through the use of Gabor Filter. As for the classification algorithm used, it is an SVM algorithm with the use of RBF. Accuracy obtained was 98.5 % for satellite images.

Guofeng Sheng, Wen Yang, Tao Xu a & Hong Sun [4]: This research deals with the method of classification of high-resolution satellite images scenes. A variety of methods have been used to extract features which include three techniques: color histograms, LTP-HF (Local Ternary Patterns histogram Fourier) and SIFT (scale invariant feature transform). These features were combined to obtain a high classification accuracy. The first two stages were combined using the linear SVM classifier, which was first used to generate the probability of images using the three methods mentioned. The resulting probability images in the second stage are used for classification. Through the proposed classification methods, a great performance was achieved for the classification.

**Elise Desmier, Frederic Flouvat, Benoit Stoll and Nazha Selmaoui-Folcher [5]:** In this research, a method of classifying high-resolution satellite imagery was provided by using 306 images of the Tuamotu archipelago. The decision trees of data mining techniques were applied to the RGB binary analysis to improve classification performance.

**Satellite Images**

Satellite images are stored in raster format. This format is suitable for analysis because a value has an accessible location. When the satellites that observe the Earth take an image, they read and record the reflection values. These values are collected from wavelengths along the electromagnetic spectrum. The human eye sees small parts of the light energy that form the electromagnetic spectrum. This light that the human eye can see is called visible light. However, satellite sensors see a much wider spectrum than the electromagnetic spectrum. Its ability to gather information outside our natural range of vision, this made the previously invisible things visible today. The wavelengths are different, so the sensors give priority to gathering information from different wavelengths of the spectrum. Each section of the spectrum that is captured and classified by the sensor is classified as a band These bands vary in size and can be combined to produce a visible image, such as IKONOS image comprises of four bands: Blue, Green, Red and Near Infrared [6]. Satellite images can be classified into several types according to a spatial resolution which are low resolution, medium resolution and high resolution [7].

**Preliminaries**

**1. Feature Extraction**

Feature Extraction (FE) is a significant component of each Image Classification. Set the image pixels in the feature field is known as feature extraction. For automatic identification of the objects from images, they are to be related to specific features which characterize them with each other [8].

**a. Color Features**

It considers one of the most significant features that helps humans to recognize and understand the image easily. There are several techniques for representing color features such as color moments, color histogram etc. [8]. Color histogram as we know, the RGB system is represented by the blending of the three primary colors red, green and blue. In this model, the calculation of features such as mean, standard deviation, and energy is calculated from each color plane in this model RGB these three colors provide information related to histogram distribution of the three-color plane in RGB model. each of these three colors has 256 levels, that Meaning there will be 256 various inputs in the histograms for each plane, to calculate the features the first order histogram probability P(g) need to define firstly, which define in equation 1 [9].

$$P(g) = \frac{N(g(i))}{MN} \quad (1)$$

Where N(g(i)) represent is the number of pixels at gray level g. MN is the number of pixels found in an image. Features that can compute from histogram:

**Mean**

This feature represents the average value, giving information about the overall brightness of the image, it defines by the following equation 2 [9]:

$$\textbf{Mean} = \sum_{i=0}^{L-1} g.P(i) \tag{2}$$

L represents a gray level value.

**Standard deviation**

The standard deviation is called the square root of the contrast, showing the contrast of the image. It shows the spread of data, the image with a high standard deviation has a high contrast ratio [9], the standard deviation is defined as follows equation 3:

$$\textbf{standard deviation}\ (\sigma_g) = \sqrt{\sum_{g=0}^{L-1}(g-\mu)^2 P(g)} \tag{3}$$

**Skewness**

This standard measures the symmetry around the mean in the gray level distribution. If skewness equals zero, the histogram is symmetric about the mean [9]. It is defined in the equation 4:

$$\textbf{Skewness} = \frac{1}{\sigma^3} \sum_{g=0}^{L-1}(g-\mu)^3 P(g) \tag{4}$$

**kurtosis**

This criterion represents histogram sharpness, given by the following equation [9]:

$$\textbf{Kurtosis} = \frac{1}{\sigma^4} \sum_{g=0}^{L-1}(g-\mu)^4 P(g) \tag{5}$$

**Energy**

The energy represents the distribution of pixel levels in the image. If the energy value is 1, this region has a fixed pixel level. Otherwise, if the energy value is lower, the pixel values are distributed at larger levels of color pixels [6], it shows in equation 9.

$$\boldsymbol{Energy} = \sum_{g=0}^{L-1} [\boldsymbol{P}(\boldsymbol{g})]^2 \qquad \textbf{(6)}$$

**b. Texture Features**

The texture is a very important description of a large set of images. It considers that the human visual system uses a texture for the purpose of interpretation and discrimination. This method is characterized by other methods that are measured from a set of pixels while the color is a pixel property. [10]. From common techniques used in texture features, we deal with two techniques.

**i. Gray Level Co-occurrence Matrix (GLCM)**

Gray level co-occurrence matrix (GLCM), it is one of the most important and famous methods used to extract texture features. This matrix is defined by relying on the common probability of two or more pixels for different positions. This method does not show the properties of the brightness distribution, but it shows the position of the pixels that have the same brightness [11]. For the digital image I of dimension M × N which is expressed I (x, y) let dt denoted to distance between pixels. Its gray level is described as: P ( i, j |dt, $\theta$), $\theta$ is the angel between the pair of gray level and the axis. $\theta = 0^{\circ}, 90^{\circ}, 45^{\circ}, 135^{\circ}$ four direction. So this Gray level Co-occurrence is described as P ( i, j |dt,$\theta$), according to the distance dt and the angle. Figure 1 illustrate GLCM.

| | | | |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

(a)

| | | | |
|---|---|---|---|
| (0,0) | (0,1) | (0,2) | (0,3) |
| (1,0) | (1,1) | (1,2) | (1,3) |
| (2,0) | (2,1) | (2,2) | (2,3) |
| (3,0) | (3,1) | (3,2) | (3,3) |

(b)

| | | | |
|---|---|---|---|
| 4 | 2 | 1 | 0 |
| 2 | 4 | 0 | 0 |
| 1 | 0 | 6 | 1 |
| 0 | 0 | 1 | 2 |

(c)

| | | | |
|---|---|---|---|
| 6 | 0 | 2 | 0 |
| 0 | 4 | 2 | 0 |
| 2 | 2 | 2 | 2 |
| 0 | 0 | 2 | 0 |

(d)

| | | | |
|---|---|---|---|
| 2 | 1 | 3 | 0 |
| 1 | 2 | 1 | 0 |
| 3 | 1 | 0 | 2 |
| 0 | 0 | 2 | 0 |

(e)

| | | | |
|---|---|---|---|
| 4 | 1 | 0 | 0 |
| 1 | 2 | 2 | 0 |
| 0 | 2 | 4 | 1 |
| 0 | 0 | 1 | 0 |

(f)

**Figure 1:** Example illustrate Gray Level Co-occurrence Matrix ,(a): 4 *4 image ,(b):gray tone ,c=0,d=90,e=135 ,f=45.

Haralik proposed fourteen features of the texture that are calculated from the probability matrix based on co-occurrence matrix from this feature [12]:

### Energy

which can be defined as the sum of the squares of entries in the GLCM.it measured homogeneity of the image. When the value is high, the image has high homogeneity., it denoted by equation 7 [12]

$$\boldsymbol{ASM = \sum_{i=0}^{M}\sum_{j=0}^{N} P_{ij}^{2}} \qquad \textbf{(7)}$$

### Contrast

This feature is used to measure the contrast of the image as it measures the local differences. If the image has a high contrast, the contrast value will be high as shown in equation 8 [12].

$$\boldsymbol{ASM = \sum_{i=0}^{M}\sum_{j=0}^{N}(i-j)P_{ij}^{2}} \qquad \textbf{(8)}$$

### Correlation

This statistic denotes the measure of gray tone linear dependencies in the image [13].

$$cor = \sum_{i=1}^{M} \sum_{j=0}^{N} \frac{(i - mean_i)(j - mean_j)P_{ij}}{\sigma_i \, \sigma_j} \tag{9}$$

**Homogeneity**

Homogeneity is a measure of the closeness of the distribution of elements in the GLCM. [12]

$$Homog = \sum_{i=0}^{M} \sum_{j=0}^{N} \frac{p_{ij}}{1+|i-j|} \tag{10}$$

**ii. Local Binary Patterns (LBP)**

LBP is an approach used in images to describe textures and extract texture features. LBP became more popular and applied in many application areas. According to good performance results in image texture and image representation. There are two major reasons that make local binary patterns is popular. The first reason, it is robust to gray level changes.

The second reason, it is a fast and efficient approach to calculating image features. Local binary patterns method applies a mask on the image to get a new pixel value to the mask's center pixel this done by scanning the neighborhood pixels. In this method, binary code is generated by chosen the middle pixel as a threshold value comparing it with neighborhood pixel values. The neighborhood values that are greater or equal to center value return 1 and neighborhood values that are smaller than threshold value return 0. when the binary code is generated It is turning into a decimal value. This value obtained is placed in the center pixel of the image [14].

The initial version of LBP works in a (3 × 3) pixel block of an image. When the pixel in this block are threshold by the center pixel value, it is then multiplied by powers of 2 and then sum operation done to get a label for the center pixel [15]. Figure 2 shows LBP operator. A histogram of the image is calculated after local binary patterns mask convolves the whole image and updates pixel values. In this histogram, each value is denoted by a histogram bin, then the image is represented by these histogram values.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 3 | 5 | | 0 | 0 | 1 | Binary code | 1 | 2 | 4 |
| 12 | 5 | 2 | → | 1 | | 0 | 00101011 | 8 | 5 | 16 |
| 6 | 3 | 4 | | 1 | 0 | 1 | | 32 | 64 | 128 |

LBP= (0*1) +(0*2) +(1*4) +(0*16) +(1*128) +(64*0) +(32*1) +(8*1) =172

**Figure 2:** LBP process

## 2. Feature Normalization

This process involves transforming attributes into a form in which they are within a specific range such as [0.0, 1.0]. The normalization process is useful for classification algorithms in particular such as an algorithm Nearest neighbor and neural network algorithm, Where the process of features normalization, help these algorithms to accelerate the training phase. features normalization includes several ways from these z score normalization This process involves calculating the average values first and then calculating the standard deviation of the features and then normalization is done through this equation:

$$\boldsymbol{Z_i} = \frac{z_i - \bar{x}}{\sigma_x} \qquad \textbf{(11)}$$

Where $\bar{x}$ represent mean of features, $\sigma_x$ stander devotion. This method is useful when the maximum and minimum value of the features is unknown or when there are extreme values [16].

## 3. Feature Selection

The selection of irrelevant features leads to a trouble in the work of the classifier and therefore the results may be incorrect. So, the Feature Selection plays an important role to enhance the accuracy and efficiency of the classifier. This process involves selecting sub-features from the original features by removing all the redundant and unrelated features. Feature selection lessens the dimensions of the features and increases learning accuracy and improves results. Techniques for feature selection are classified into two categories: filter methods and wrapping methods, it belongs to filtering methods. It is a measure of the dependence between the random variables. The value of MI is zero if the variables are independent. Where MI between two random variables E= $(e_1, e_2 \dots e_i)$ and F= $(f_1, f_2 \dots . f_j)$ it represents as follow [17]:

$$\boldsymbol{MI(E,F) = \sum_e^i \sum_f^j p(e,f) log \frac{p(e,f)}{p(e)p(f)}} \quad \textbf{(12)}$$

## 4. Supervised Classification

The classification is defined as the formation of data into classes, which is called supervised learning. The classes are defined in advance before the data are examined. Classification algorithms require that classes defined are based on data attribute values [18]. The classification process is summarized in two steps: the first step involves the training step while the second step involves testing where the model is used to predict the class label of the given data [16]. Two model is used for classification given data as follow:

### i. Support Vector Machine

This algorithm was introduced by Cortes and Vapnik, (1995) to solve classification problems and regression. It is based on the theory of statistical learning. It works to find the optimal hyperplane, which maximizes the margin between the classes. This algorithm is one of the methods of supervised classification, where a set of inputs are given with their labels, the forms of these inputs represented by attributes vector. As mentioned previously, this algorithm works to create a hyperplane to separate the two types to achieve the maximum separation between these classes. In Fig 3, two planes parallel to the classifier that pass through several points are termed ‘bounding planes. The distance between these two planes is called the margin. The points on the bounding planes are known as ‘support vectors’.

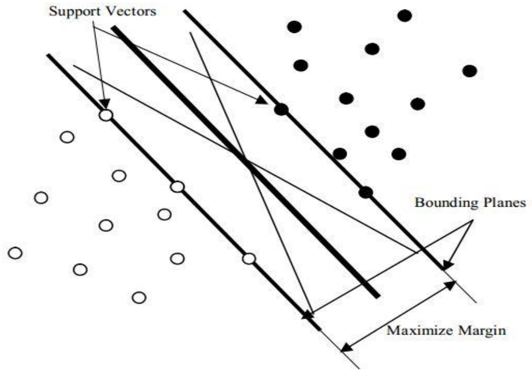


**Figure 3:** SVM Hyperplanes between two classes

SVM algorithm is classified into two types: linear and nonlinear as will illustrate in the following sections [16].

### A. Linear SVM

If the hyperplane of the SVM is linear then such an SVM is known as linear SVM. For example, if z represent training pairs ($x_i$,$y_i$) where i=1,2... z, with the class labels y ∈(1,-1). hyperplane defined by the following equation:

$$\boldsymbol{w.x+b=0} \quad \textbf{(13)}$$

W represents a weight vector, W= $\{w_1, w_2, \ldots w_n\}$, b represent bias, and x attributes. The data classifier is expressed by the following function:

$$\boldsymbol{f(x.w.b) = sgn(w \cdot x + b)} \quad \textbf{(14)}$$

f(x) is the hyperplane function in m dimensions which is given as the set of all points x ∈ $R^m$that satisfy the equation f(x)= 0, so the hyperplane function f(x) works as a linear classifier, which predicts the class y for any given point x, according to the following decision rule:

$$\boldsymbol{w^T.x+b \geq 1 \quad for \quad y = +1} \quad \textbf{(15)}$$

$$\boldsymbol{w^T.x+b \leq 1 \quad for \quad y = -1} \quad \textbf{(16)}$$

Maximizing the margin is a problem of constrained optimization, which can be solved by Lagrange Method. Each training point x_i is described by a Lagrange multiplier α:

$\alpha_i = 0 \Longrightarrow \boldsymbol{x}_i$ has no effect on the hyperplane.

$\alpha_i > 0 \Longrightarrow \boldsymbol{x}_i$ These Support Vectors points, which lie nearest to the hyperplane.

When we obtain the $\alpha_i$ value, we can then compute weight and bias, the weight compute using the following equation:

$$\boldsymbol{W} = \sum \boldsymbol{\alpha_i}\,\mathbf{x_i} \qquad \textbf{(17)}$$

the points with $(\alpha_i = 0)$ consider not support vector, so the summation of support vector that its $(\alpha_i)$ not equal to zero will be taking, where support vector with $(\alpha_i = 0)$ does not play any role in determining [16].

### B. Nonlinear SVM

Linear classification in most cases fails to find the optimal classification solution for that nonlinear classification in such cases is used. Where it is used a nonlinear kernel function [17].

### C. kernel methods

kernel functions are introduced to transfer training and testing samples to a high-dimensional feature space. In this part, kernel functions are presented to exchange mapping functions, because the kernel calculation is more efficient than the mapping function, so computing time can be commonly saved by employed kernels to replace mapping functions [19]. The Commonly used kernel functions are:

**Linear**

$$\boldsymbol{k(x.x_i) = (x \cdot x_i)} \qquad \textbf{(18)}$$

**Polynomial of degree d**

$$\boldsymbol{k(x.x_i) = (x \cdot x_i)^d} \qquad \textbf{(19)}$$

**Radial Basis Function (RBF)**

$$k(x.x_i) = exp\frac{-\|x-x_i\|^2}{2\sigma^2} \quad (20)$$

RBF kernel depended in our work.

### D. Multi-class SVM

The original form of the SVM algorithm is designed to classify two types of classes, but in real life, there are situations that require the separation of more than two class. Therefore, to solve this problem, will illustrate two concepts with k classes (k>2) [19]: One against all, this approach contains M binary class, where one class is trained with all data, where this class is positive and other classes negative [20]. One-against-one multiclass SVM, this concept generates M(M-1)/2 binary classifier where each one is trained on data of two classes for M class in a dataset. [20]. In our paper one against all used for classifying eight class that will mention later.

### ii. K-Nearest Neighbor

The KNN algorithm is one of the simplest and most important in data mining, despite its simplicity, but it works well. This algorithm is known as the lazy learning algorithm. It is also nonparametric, meaning that it does not put any assumptions on the distribution of basic data. The algorithm is lazy because it does not use training data to make any generalization.

This means that there is no training phase or very few, this gives speed at the time of execution. Lack of generalization means that all training data are retained, so all training data is required at the testing stage. The method of classification of this algorithm depends on the selection of the closest samples in the feature space. Where the object is classified by a majority of the votes of neighbors and this is called the nearest neighbor by using the distance, Various distance metrics can be used when calculating distances for the KNN algorithm [21].

## Proposed Work

The proposed methods involve several stages to classify the scene of satellite images. The main objective is to apply classification methods for high-resolution satellite scenes using multiple features and gain high classification accuracy. Figure 4 shows these stages, which will be explained at next in each section.

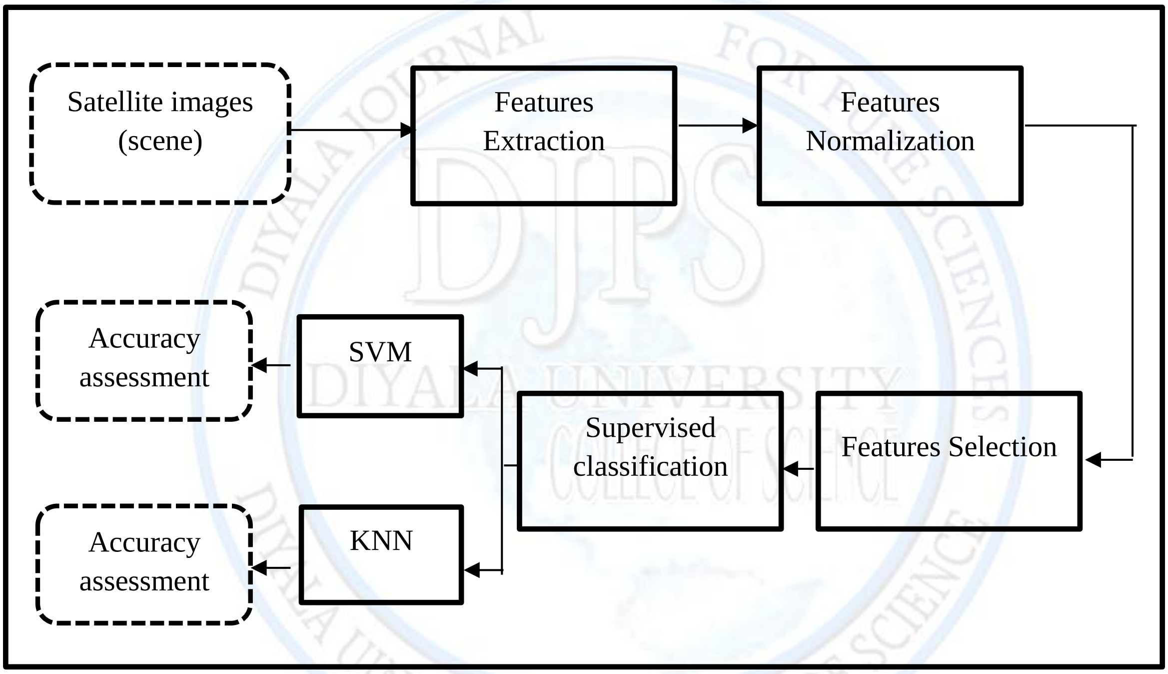


**Figure 4:** Classification Structure

After image read, features are extracted by using two techniques color histogram features and texture features using LBP and GLCM. In GLCM four features were extracted (Contrast, Correlation, Energy, Homogeneity). While in LBP 36 features obtained from this algorithm using rotation invariant mapping, thus leading total features to 58 from three techniques which were mentioned.

After features extraction normalization steps made then features selection method applied, in this step 35 features selected depending on mutual information method then two techniques of classification applied SVM and KNN for classification the given classes.

## Accuracy assessment and results

The data used in our work includes 8 class, each class contains 100 images, 80% of which were used as training data and 20% for testing the classes are: airport, rivers, baseball diamond, Parking lot, beach, freeway, dense residential and bridge. Figure 5 illustrates testing data that used in system 20 scene images are taken from each class for testing. Accuracy computed for each class and also average time for two algorithms are computed.


**Figure 5:** Satellite images used as testing for classifier

Size of each image is 256×256. To calculate the accuracy of the SVM and KNN we use the following equation. This equation provides the accuracy ratio to the classified images.

$$Accurcy = \frac{\text{number of correctly classified images}}{\text{total number of images}} \times 100\% \qquad \textbf{(21)}$$

Table 1 shows the results of two algorithms and figure 6 show comparison of the two algorithms.

**Table 1:** Accuracy of SVM and KNN

| Class Label | Class name | Accuracy | |
|---|---|---|---|
| | | SVM | KNN |
| 1 | River | 85% | 80% |
| 2 | Airport | 85% | 80% |
| 3 | Baseball diamond | 80% | 75% |
| 4 | Parking lot | 85% | 75% |
| 5 | Beach | 85% | 80% |
| 6 | Bridge | 85% | 80% |
| 7 | Freeway | 95% | 75% |
| 8 | industrial area | 90% | 85% |

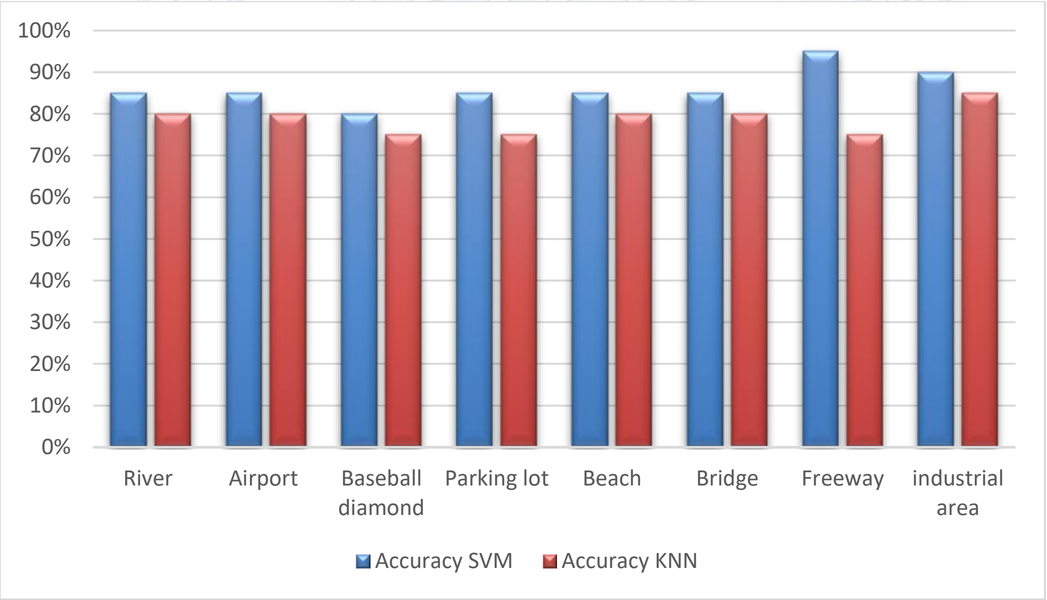


**Figure 6:** SVM and KNN accuracy

## Conclusion

In this research, introduced the method of classification of a high-resolution satellite image (scenes images) for eight class which are: river, airport, baseball diamond, parking lot, beach, bridge, freeway and industrial area class. Where the features of texture and color play an important role in the classification of these images, and the use of three techniques of features extraction help to improve the accuracy of the classification. Some misclassification accrues because of overlap in areas in each class, so reject class is defining to any image that not respond to the area found in the testing image. Through the results obtained showed that the SVM classifier gave better results for classification than the KNN classifier and the implementation time to KNN less than SVM classifier where it took longer. In this research, we obtained a high accuracy degree of classification through the use of satellite images using multiple algorithms that contribute to obtaining excellent results.

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