

Optimization for Supervised Satellite Images Classification

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Abstract:- Remote sensing is a method of detecting and inspecting the characteristics of objects. It uses magnetic energy within the range of heat, light, and radio waves. Very different applications that use remote sensing are agribusiness, disaster dashboards, water management, etc. The strategy of creating thematic maps based on remote imagination is called imageclassification. For at least one phantom computer, the extended number usually represents spectral information. Used to classify images. This data is used to classify individual pixels on the spectrum. Used for classification. This article introduces a classifier specifically controlled by a minimum distance, maximum likelihood, and parallelepiped. By using PSO technology (particle swarm enhancement), we can achieve better results. Constant letters and general precision. Sentences: classification, confusion nets, letter coefficients, total accuracy, parallel classifiers, remote sensing, improved methods.

Keywords:- Classification, Confusion Matrix, Kappa Coefficient, Overall Accuracy, Parallelepiped Classifier, Remote Sensing, Optimization Techniques.

I. INTRODUCTION

The scientific and analytical information about the spectacle, location, or element used by the equipment without physical contact with the area is considered remote sensing technology. Remote sensing is used for satellites. They are used for settlement through the area. The energy is released or reflected by the target. Remote sensing estimates the reflected and emitted in the spectral range. Discrete spectral range. It is understandable because of the spectral range. Special range, when data is collected across multiple spectra, it is called multispectral or hyperspectral information. Satellite images can provide extensive geographic information about the area in a relatively short period. Land area, geology, soil grouping, ocean, etc., High spatial resolution images can provide detailed target information. Abstract and high-resolution spectral satellite images are widely used in urban planning, cartography, gardening, and environmental management, the spatial details in such a symbology are limited by the number of pixels. In satellite imagery, all pixels are usually classified as one of the land cover categories. Device image classification creates a subject map with remote recognition images. The generated map represents various features on the surface, such as Vegetation, buildings, and streets.

Different satellite sensors produce images of different quality. There are four ways to classify images: The first is image preprocessing, the second is to select specific criteria to improve the structure, select a classifier, and finally evaluate the accuracy of image classification. Image classification is usually performed using supervised and unattended classification. The classifier needs to have prior knowledge of the research field under the guidance of the curator. In supervised classification, image analysts choose training pixels. These pixels usually have different land cover attributes. Using these options, the classification is complete. The automatic classification does not require any prior information about the study area. In this classification process, quiet, large unknown pixels will be examined, and they will be further divided into completely different categories based on the natural grouping of the image. Select the training data image without analysis.

II. PROPOSED SYSTEM

2.1 Support Vector Machine (SVM)

In the basic SVM file, predictions will be calculated for the specified input data. There are two possible classes to support this conclusion. The SVM model is used to represent points in space. They are coordinated so that the transparent gap between samples of different categories should be as wide as possible. These examples show different time displays in the same area. SVM uses kernel mapping to map the knowledge in the input space to the multidimensional feature space. Therefore, the substance is currently linearly separable. The number of passing DM and its weight. In the figure below, SVM separates these two categories. Any destination on the left side of the right belongs to the blue square category. This is the role of SVM: it finds a line/hyperplane (multiple dimensional spaces that separate classes).

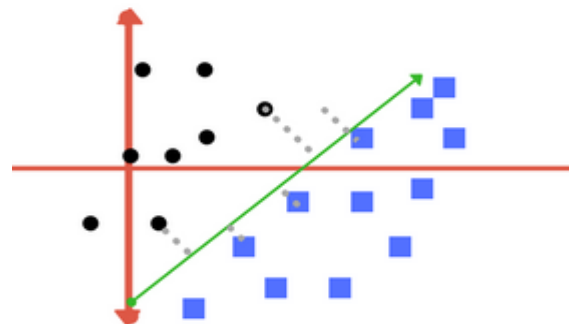


Fig 2.1: Classification of two classes using SVM

2.1.1 Regulation of SVM

The fundamentals of Support Vector Machines and also the way it works are best understood with an easy example. we could say we've two tags: red and blue, and our data has two features: x and y we'd kind of a classifier that, given a pair of (x, y) coordinates, outputs if it's either red or blue. We plot our already labeled training data on a plane

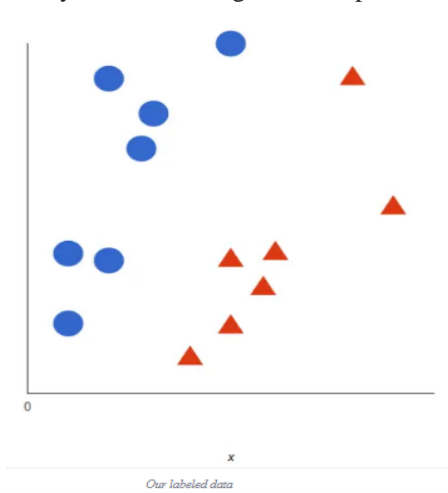


Fig 2.2: plotting labeled training data on a plane

A support vector machine takes these data points and outputs the hyperplane (which in two dimensions it's simply a line) that best separates the tags. This line is the decision boundary: anything that falls to one side of it we will classify as blue, and anything that falls to the other as red.

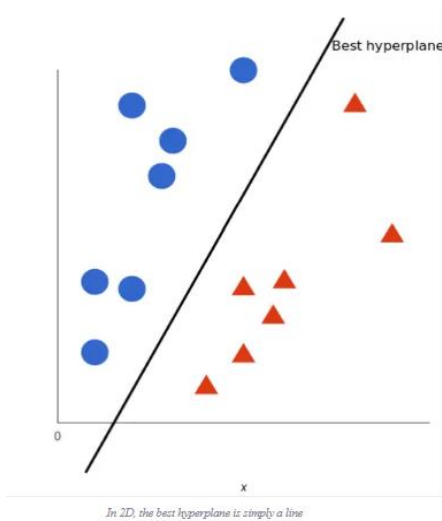


Fig 2.3: classification using a decision boundary (hyperplane)

But, what exactly is the best hyperplane? For SVM, it's the one that maximizes the margins from both tags. In other words: the hyperplane (remember it's a line in this case) whose distance to the nearest element of each tag is the most largest.

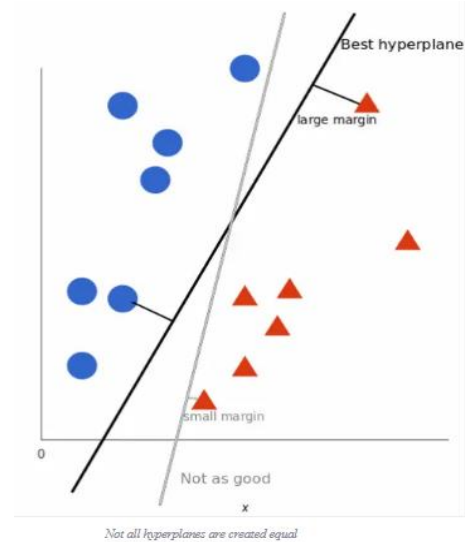


Fig 2.4: decision boundary (hyperplane) drawn nearest to the elements

Now this instance was easy, since clearly the info was linearly separable — we could draw a line to separate red and blue. Sadly, usually things aren't that simple. Take a glance at this case:

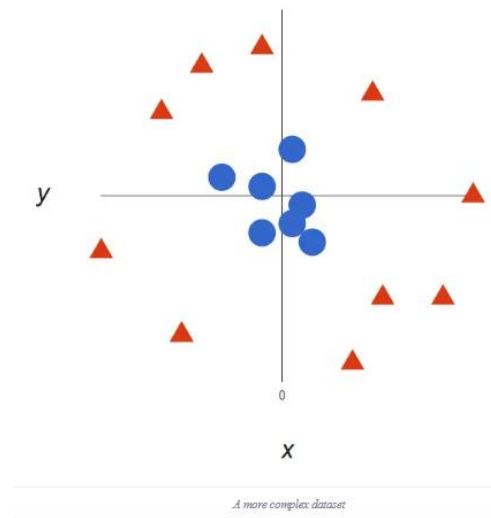


Fig 2.5: Complex data (non-separable)

It's pretty clear that there's not a linear decision boundary. However, the vectors are segregated and it's as if it should be easy to separate them. So, here we will add a third dimension. until now we had two dimensions x and y. We create a new z dimension, and: $z = x^2 + y^2$ (you'll notice that's the equation for a circle). This will give us a three-dimensional space. Taking a slice of that space, it looks like this:

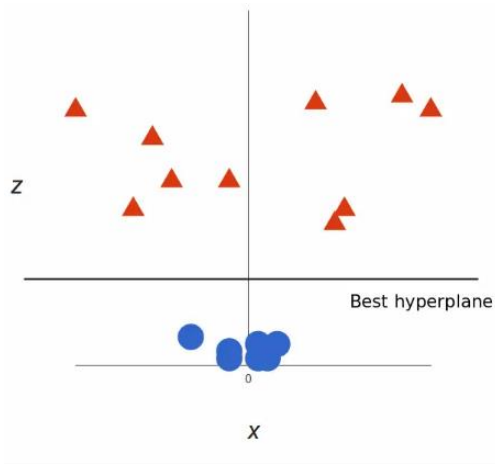
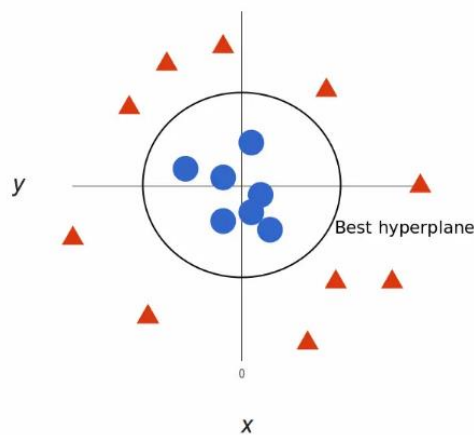


Fig 2.6: Slicing the complex data

The hyperplane could even be a plane parallel to the x axis at a certain z (let’s say z = 1). What’s left is mapping it back to two dimensions:



Back to our original view, everything is more neatly separated

Fig 2.7: Drawing curved decision boundary (hyperplane)

right here! The limitation of our solution can be a circle with a radius of 1, which uses SVM to separate two labels

2.2 Particle Swarm Optimization (PSO)

PSO is similar to evolutionary computing methods (such as genetic algorithm (GA)). GA uses a series of random solutions for initialization. And strive for the best self-renewing generation. However, unlike GA, PSO does not contain evolutionary operations such as crossover and mutation. In PSO, potential solutions called particles fly over matter. The space behind these best particles. For details, see the following sections. Compared with GA, the advantage of PSO is that PSO is easy to implement and many parameters must be adjusted. PSO has been successfully applied in many fields: improvement, artificial neural network training, fuzzy system management, and various fields where GA is used. There are two group-based standard strategies in process mining: Alphabet Colony Organization (ACO) and PSO. ACO is inspired optimization problems. The main goal is to schematically simulate the choreography of birds or fish.

However, it has been found that the particle swarm model is often used as the optimizer

2.2.1 The Algorithm

The PSO algorithm simulates the behaviors of a flock of birds. Assume the following situation: a flock of birds randomly chooses nearby food. Just a piece of food to find in the kingdom. Not all birds know where the food is. But they know that food is like every iteration. What is the best strategy for foraging? Paying close attention to the birds closest to the food is the most effective. PSO learns from this script and uses it to solve optimization problems.

In PSO, each solution can even be a bird in the search space. “particle”. The fitness value of all particles is evaluated by the fitness function for optimization, and its speed determines the flight of the particles. The particles fly in the physical space and follow the best existing particles. initialize the PSO with a set of random particles (solution), then search for the best particle and update the generation. At each iteration, each particle is updated based on the two “best” values. Most importantly, so far, the only solution (skill) has been achieved. The value is also saved. It is said that this value is the best. Another “best” value followed by the particle swarm optimizer is that this is the only value it has obtained for particles in the population so far. The value for money is also the best in the world, known as guest houses. Regarding the neighborhood of the population as its topological neighborhood, the unique value is also the best neighborhood, so it is called better. After finding the 2 best values, the particle will update its velocity and position using the following equation

$$v[i] = v[i] + c1 * rand() * (pbest[i] - present[i]) + c2 * rand() * (gbest[i] - present[i])$$

$$present[i] = present[i] + v[i]$$

v[] is the particle velocity, present[] is the current particle (solution). pbest[] and gbest[] are defined as stated before. rand() is a random number between (0,1). c1, c2 are learning factors. Usually c1 = c2 = 2.

III. DESIGN FLOW CHART

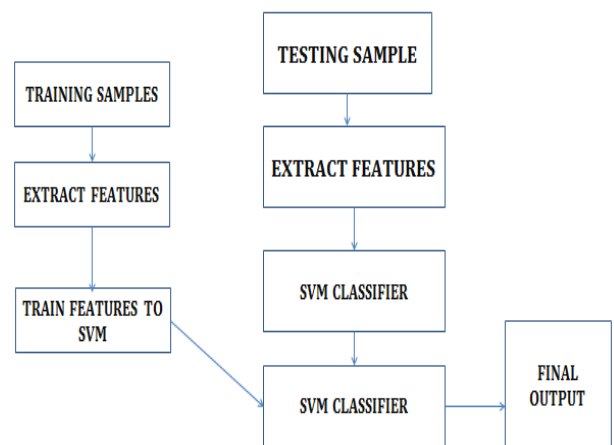


Fig. 3.1: System Design Flow Chart

IV. RESULT ANALYSIS

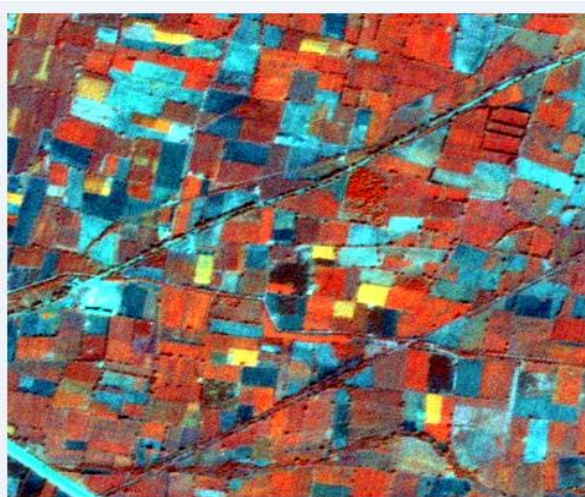


Fig 4.1: Input Satellite Image

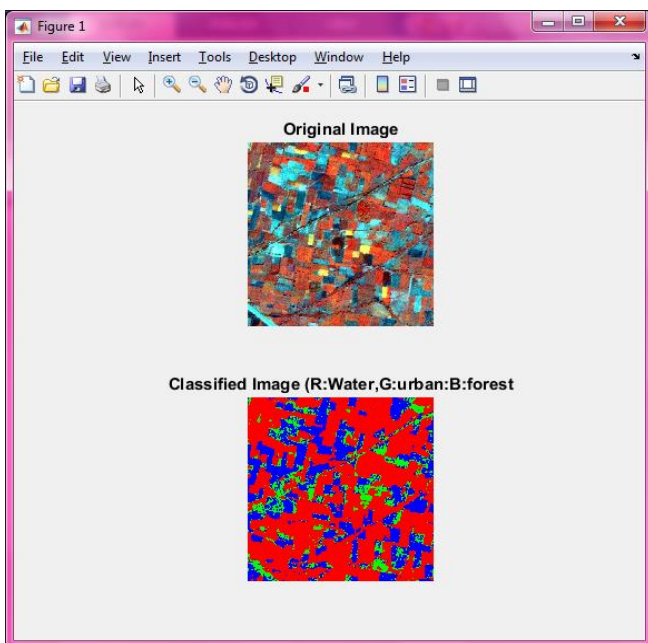


Fig 4.2: Classified Image output

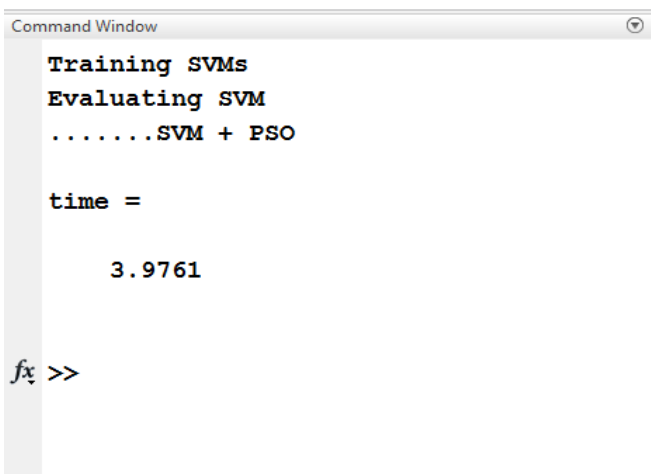


Fig 4.3: Command Window display of Outputs

V. CONCLUSION

This paper examines various supervised classification approaches and methods, as well as post-classification algorithms and the idea of using cellular automata and contextual classification to classify satellite images. Satellite image classification is a field with a lot of applications in socioeconomic and environmental areas. Information such as cadastral information, land cover type, vegetation type, and soil properties could be obtained by classifying satellite imagery. The various approaches discussed in the literature review rely on different strategies and each has its own collection of benefits and disadvantages. They can, however, be used for a variety of applications. The traditional classification algorithms in combination with other Lear, the use of other learning methods in conjunction with traditional classification algorithms was explored. Different post-classification strategies were also explored in the studies. In addition to spectral classification, the role of contextual classification and its importance in classifying images with a high degree of heterogeneity were investigated. The comparative analysis came to the conclusion that the large Classification accuracy rating for a system combining a classical classification algorithm with cellular automata with contextual classification, which combines classification and post-classification techniques.

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