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USE OF SVM KERNEL FOR BETTER CLASSIFICATION ACCURACY FOR REMOTE SENSING DATA

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ABSTRACT

The classification of remote sensing images is a challenging task, as image contains bulk of information which is to be carefully extracted and used. Support vector machine (SVM) has proven its excellence in the field of remote sensing image classification. Using SVM as a classifier multiple kernel methods can be constructed and tested over a specified set of image dataset. In this paper, we present a framework in which multiple SVM kernels are tested on a remotely sensed image for analysis of behaviour of kernel methods over image dataset. Pre-step to image classification is feature extraction on the basis of which image is classified. In our system, the image is classified into two classes on the basis of colour feature of image. Accuracy of each kernel along with delay in image classification is calculated for the task of kernel optimization over remotely sensed image. Thus a set of best suited kernel methods can be identified over a specific dataset.

KEYWORDS: Image classification, support vector machine, feature extraction, kernel selection, kernel optimization.

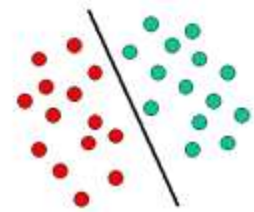
INTRODUCTION

Support vector machine has found to be best suited for remote sensing image classification. Kernel based image classification has been widely used for remotely sensed image classification. With multiple SVM kernel methods an image can be classified by different methodologies for classification which is used for performing kernel optimization. Feature extraction also plays a crucial role in image classification as image gets classified into two groups on the basis of some extracted feature. By this comparative study of kernels, we can idealize some kernel over remotely sensed image by testing kernel methods on accuracy parameter.

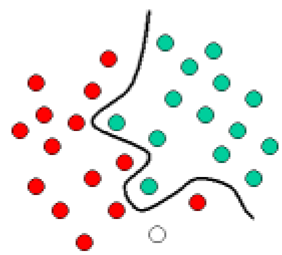
SUPPORT VECTOR MACHINE

SVM is a good candidate for remote sensing data classification for a number of reasons. Support vector machine (SVM) is a pattern classification technique proposed by Vapnik et.al. SVM attempts to minimize the upper bound of the generalization error by maximizing the margin between the separating hyperplane and the training data. Hence, the SVM is a distribution-free algorithm that can overcome poor statistical estimation. The SVM also achieves greater empirical accuracy and better generalization capabilities than other standard supervised classifiers. In particular, SVM has shown a good performance on high dimensional data classification with a small training sample. SVMs are particularly appealing in the remote sensing field due to their ability to successfully handle small training data sets [1,12].
Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. A schematic example is shown in the illustration below. In this example, the objects belong either to class GREEN or RED. The separating line defines a boundary on the right side of which all objects are GREEN and to the left of which all objects are

RED. Any new object (white circle) falling to the right is labeled, i.e., classified, as GREEN (or classified as RED should it fall to the left of the separating line).



The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line.
Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve (which is more complex than a line). Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyperplane classifiers. Support Vector Machines are particularly suited to handle such tasks [4,13].



The illustration below shows the basic idea behind Support Vector Machines. Here we see the original objects (left side of the schematic) mapped, i.e., rearranged, using a set of mathematical functions, known as kernels. The process of rearranging the objects is known as mapping.

SVM KERNELS

Some of the SVM kernels methods used in this experimentation are listed as below:

1) Linear SVM kernel

The basic function of SVM model is classification whereas linear SVM is very basic SVM kernel which classifies the feature set into two classes by drawing linear hyperplane between two classes. There should be minimal margin between this hyperplane and classified elements or these elements in the margin will be called as support vectors [1,3].

2) Sigmoid kernel

We consider the sigmoid kernel K(xi, xj) = tanh(axT i xj + r), which takes two parameters: a and r. For a ¿ 0, we can view a as a scaling parameter of the input data, and r as a shifting parameter that controls the threshold of mapping. For a ¡ 0, the dot-product of the input data is not only scaled but reversed [1,3].

3) Intersection kernel

The intersection kernel over the subsets of D by (A1, A2) = µ (A1 A2) , that is, the measure of the intersection between the two sets. This can be seen to be a valid kernel by considering the feature space of all measurable functions with the inner product defined by f1, f2 = D f1 (a) f2 (a) dµ (a). The feature mapping is now given by: A IA, implying that (A1, A2) = µ (A1 A2) = D IA1A2 (a) dµ (a) = D IA1 (a) IA2 (a) dµ (a) = IA1, IA2 = (A1) , (A2) , as required [1,3].

4) ANOVA kernel

ANOVA kernels typically use some moderate value of P , which specifies the order of the interactions between attributes xip that we are interested in. The sum then runs over the numerous terms that take into account interactions of order P; fortunately, the computational cost can be reduced to O(Pd) cost by utilizing recurrent procedures for the kernel evaluation [1,3].

5) Polynomial kernel

In machine learning, the polynomial kernel is a kernel function commonly used with support vector machines

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(SVMs) and other kernelized models, that represe
nts the similarity of vectors (training samples) in a feature space over polynomials of the original variables, allowing learning of non-linear models.

For degree-d polynomials, the polynomial kernel is defined as $K(x,y) = (x^\mathsf{T} y + c)^{d}$ where x and y are vectors in the input space, i.e. vectors of features computed from training or test samples and $c \geq 0$ is a free parameter trading off the influence of higher-order versus lower-order terms in the polynomial. When $c = 0$, the kernel is called homogeneous [1,3].

METHODOLOGY

In order to classify an image, first of all the feature extraction need to be perform on that image and according to the features support vector machine need to be manually trained for type of image sample. These trained samples will be stored in a database and with reference to this dataset an input image will be classified into two classes.

1) Feature Extraction:

For training the SVM, a specific block of image is cropped from the image to be classified, is resized into 512*512 size and its features are calculated by two methods as Extended Histogram Map and Extended Edge Map. The calculated feature vector along with its graphical view is shown in below figure:

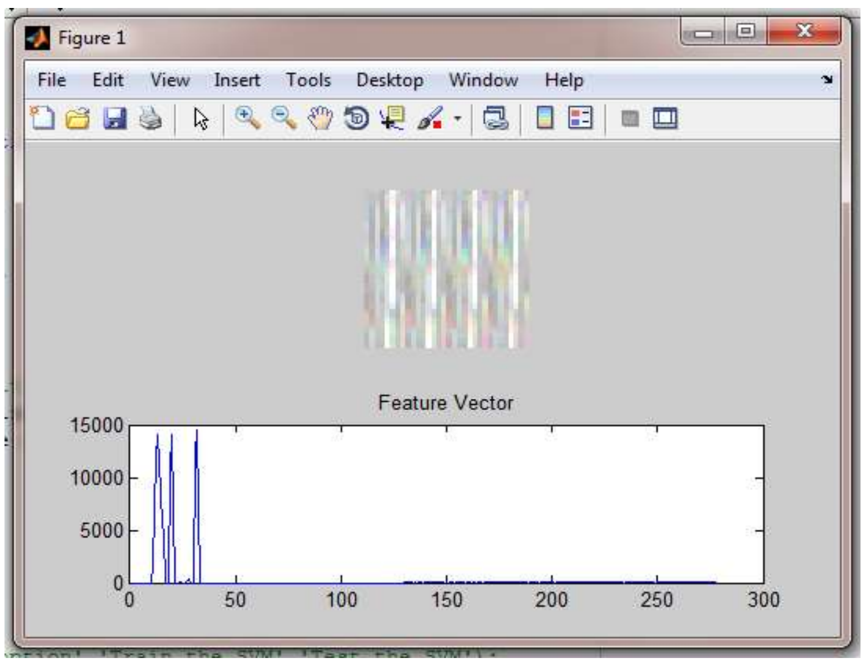
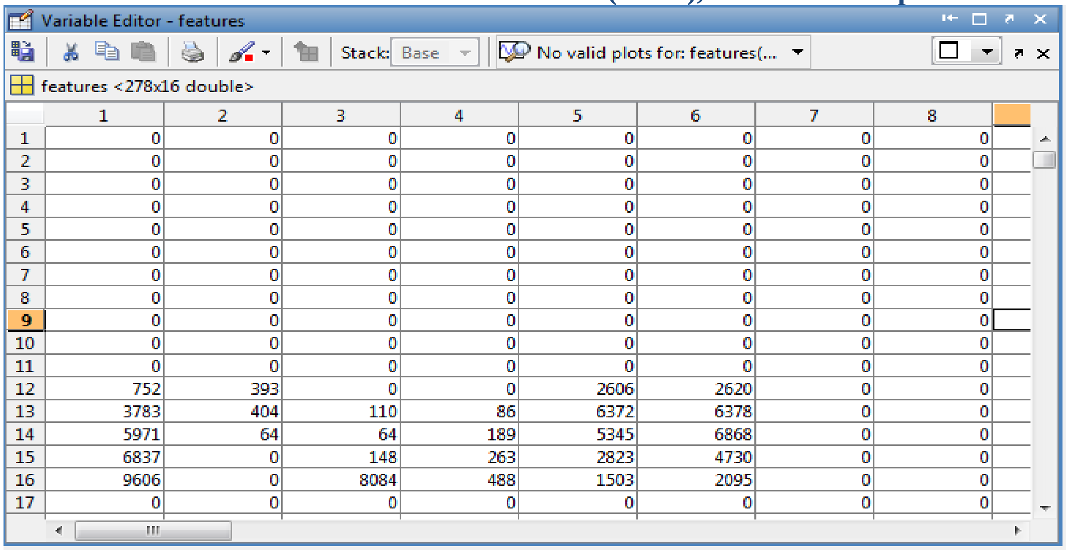


Fig 1: Graphical view of feature calculated over image block

2) Dataset Creation

The manually trained image samples are stored in a dataset and labeled as type 1 and type 2 images whereas type 1 specifies the image of agricultural land containing wheat crop and type 2 specifies the image of agricultural land containing non-wheat crop.



	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0
12	752	393	0	0	2606	2620	0	0
13	3783	404	110	86	6372	6378	0	0
14	5971	64	64	189	5345	6868	0	0
15	6837	0	148	263	2823	4730	0	0
16	9606	0	8084	488	1503	2095	0	0
17	0	0	0	0	0	0	0	0

Fig 2: Database with entries stored for each trained sample

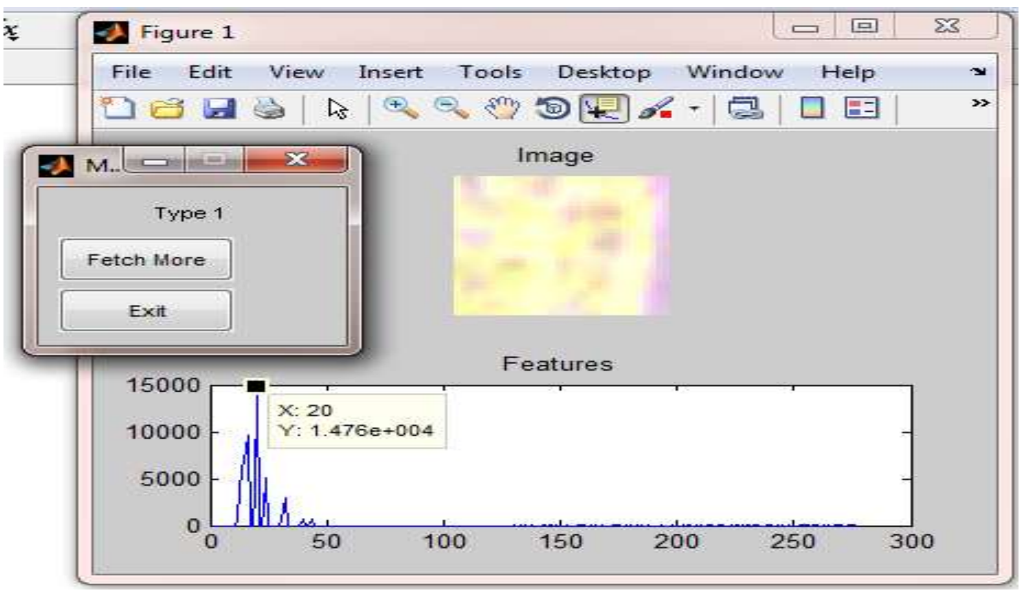


Fig 3: Database entry with graphical view of trained type 1 sample

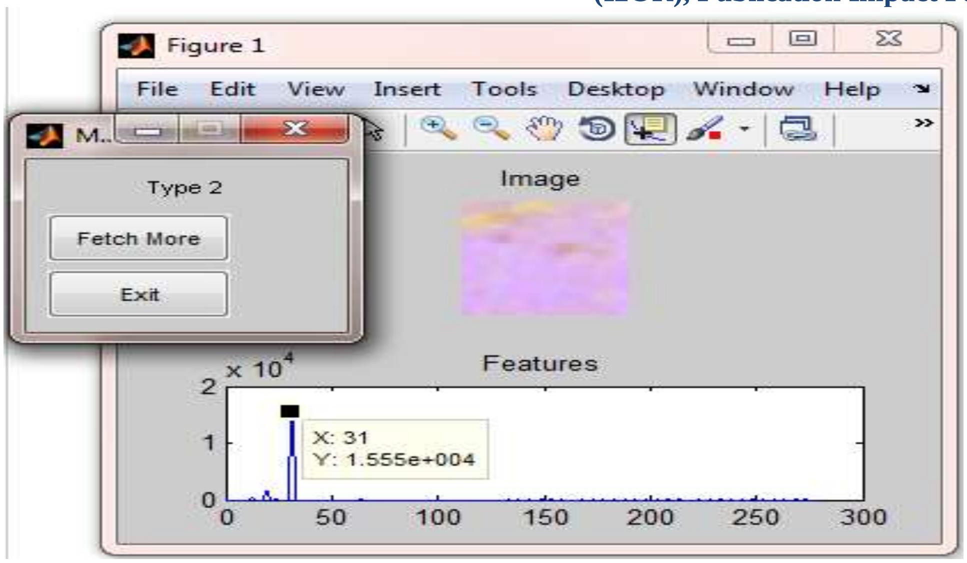
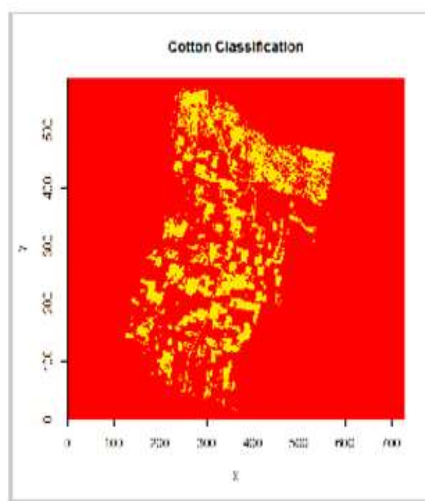


Fig 4: Database entry with graphical view of trained type 2 sample

EXPERIMENTS

For performing experimentation remotely sensed image dataset of Boregaon area has been collected. Multiple kernel methods have been applied over remotely sensed image for classification of image into two classes. Each kernel give classified image as output and classified image is compared pixel by pixel with some manually pre-classified image for calculating accuracy of kernel.

a. Original Image



b. Pre-Classified Image

There are five kernels which are implemented for image classification are Linear SVM kernel, Sigmoid kernel, Intersection kernel, ANOVA kernel and Polynomial kernel.

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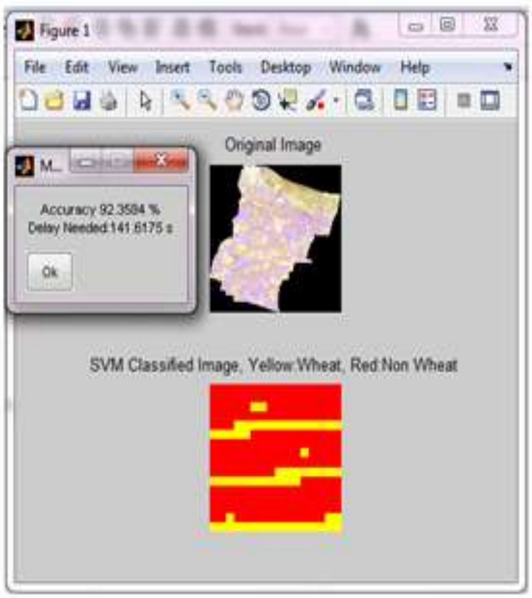
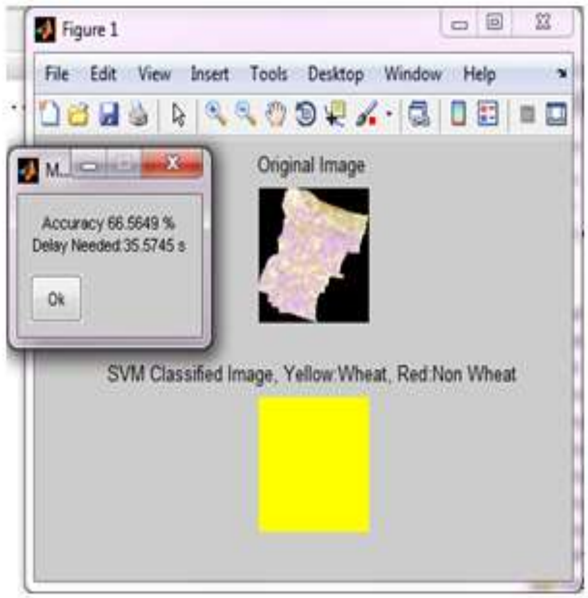
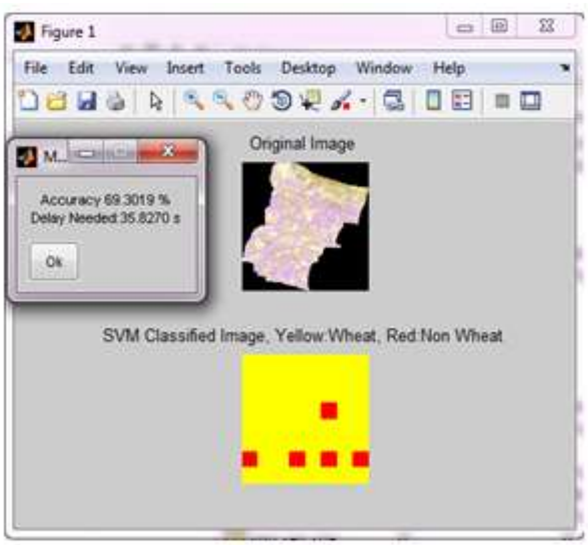
Experimental results of each of these kernels are shown in below figures:



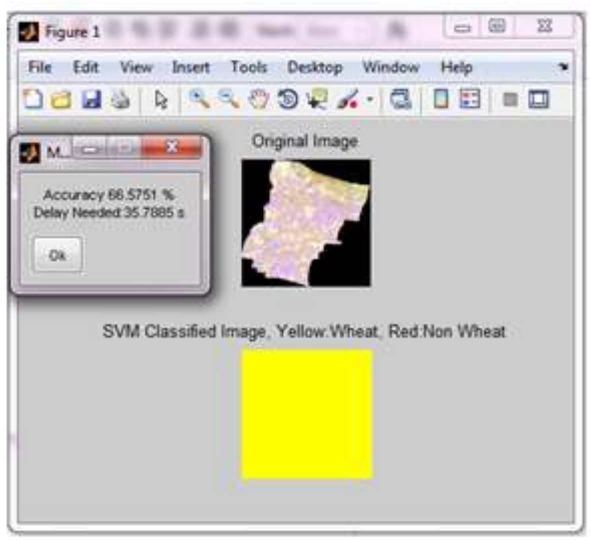
a. Linear SVM kernel



b. Sigmoid kernel



c. Intersection kernel



d. ANOVA kernel

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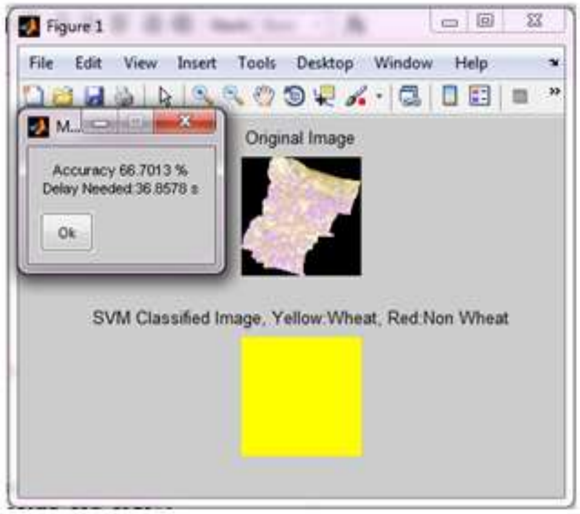

e. Polynomial kernel

The comparative analysis of kernel methods for the task of kernel optimization has been listed in below table:

Name of Kernel	Accuracy %	Time required in sec
Linear SVM kernel	92.3584	141.6175
Sigmoid Kernel	66.5649	35.5745
Intersection kernel	69.3019	358270
ANOVA kernel	66.5751	35.7885
Polynomial kernel	66.7013	36.8578

Table 1: list of implemented kernel methods along with accuracy and delay in seconds

Analysis can be inferred from the above table that Linear SVM kernel has worked well in case of classification than other kernels but the delay it has taken for image classification is also comparatively more than others.

CONCLUSION

In this paper, we propose a framework in which Support Vector Machine is used as image classifier. With more than one SVM kernel, single dataset consisting of manually trained image samples is tested. This classified output of each kernel is pixel by pixel compared with the same but manually classified image to calculate accuracy of each kernel. Along with the calculated accuracy, we also get the delay required for classification of image and these two parameters are useful for selecting best suitable kernel for our remote sensing image dataset. Among all of the tested kernels, it is found that Linear SVM kernel gives better result than other kernel but the time required for image classification is also more than expected.

In future this work can be extended by integrating our current work with framework where more than one feature has been extracted for image classification and we expect more accurate results. Moreover, any two best suitable kernels can also be integrated for getting enhanced accuracy of classification

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