Semi-Supervised Virtual Support Vector Machines with Self-Learning Constraint for Remote Sensing Image Classification

by **OZAN TUNCBILEK**

In real-world applications, it is difficult to collect labeled samples, and supervised learning methods rely on the quality of this labeled training data. Therefore, in this research, a semi-supervised learning approach is developed in order to benefit from the unlabeled samples that can be produced effortlessly. These semi-supervised methods are built on a popular machine learning technique called support vector machine, which is used to classify remote-sensing imagery in this thesis.

Moreover, the methodology is further extended with an active learning method. This extension involves uncertainty visualizations in order to increase the model accuracy by relabelling the uncertain samples in a prioritized way. To evaluate these models, experimental results were obtained over the city of Cologne, Germany, and the Hagadera Refugee Camp, Kenya from a very high spatial resolution multispectral data set.

OBJECTIVES

- Enhance accuracy properties of Virtual Support Vector Machines with Self-Learning constraint (VSVM-SL) method.
- Deploy a constrained set of unlabeled samples for model learning.
- Generate visualizations for the uncertainty of the results and monitor how the uncertainty changes with the newly developed methods.

BACKGROUND

The background of the thesis relies on a very popular semi-supervised learning approach so called Support Vector Machines (SVM) on remote sensing classification problems due to its capability of handling complex problems. The overall aim of the SVM is to establish a separating hyperplane with a maximum margin [1].

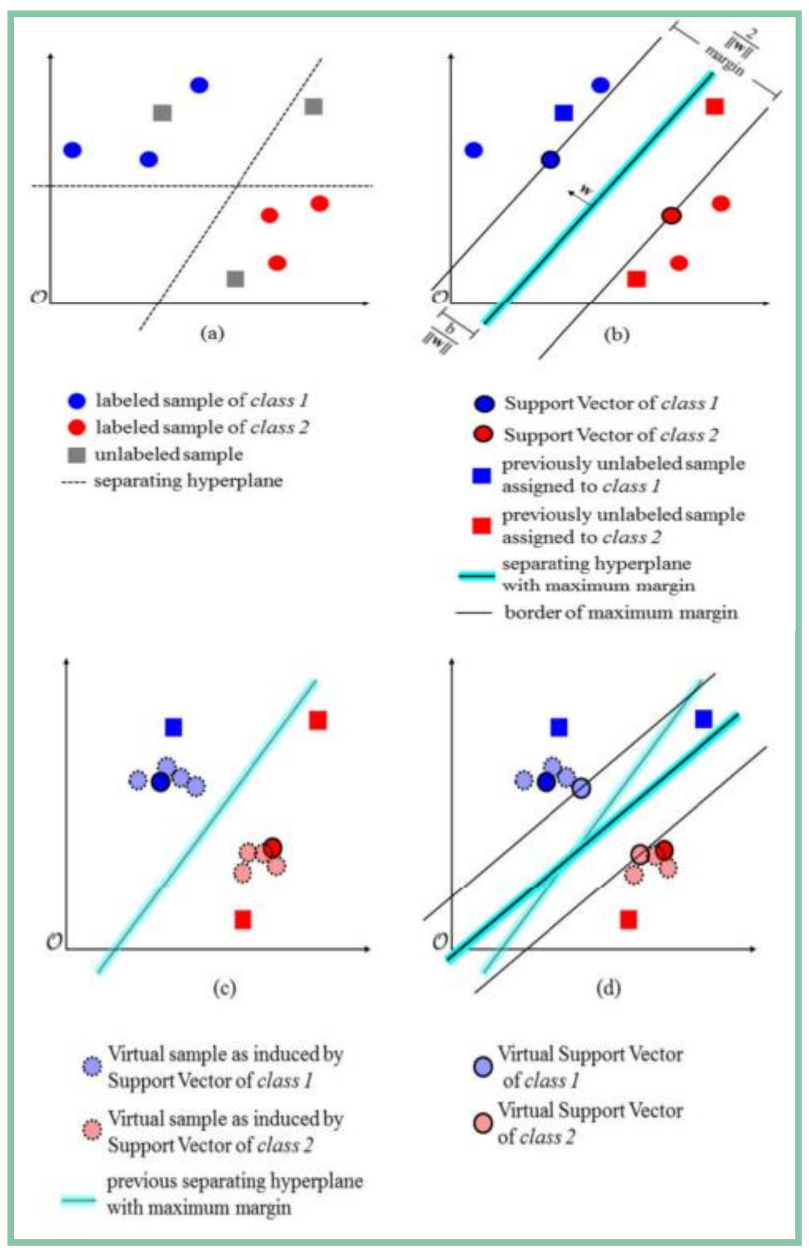
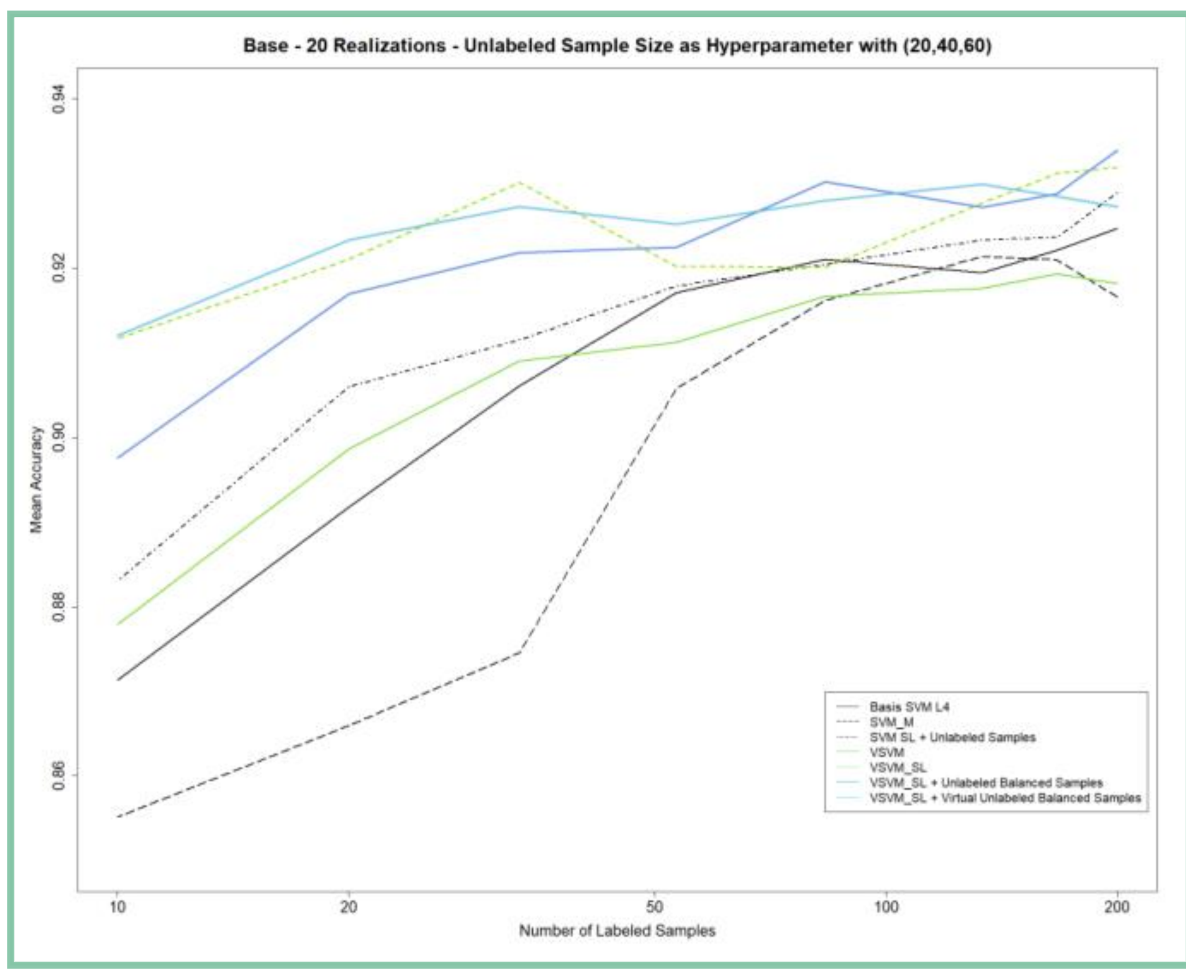


Figure 1: Working principle of VSVM approach [2]. a) Showing input vectors of different classes b) Separated hyperplane with maximum margin c), d) Altered hyperplane with virtual samples



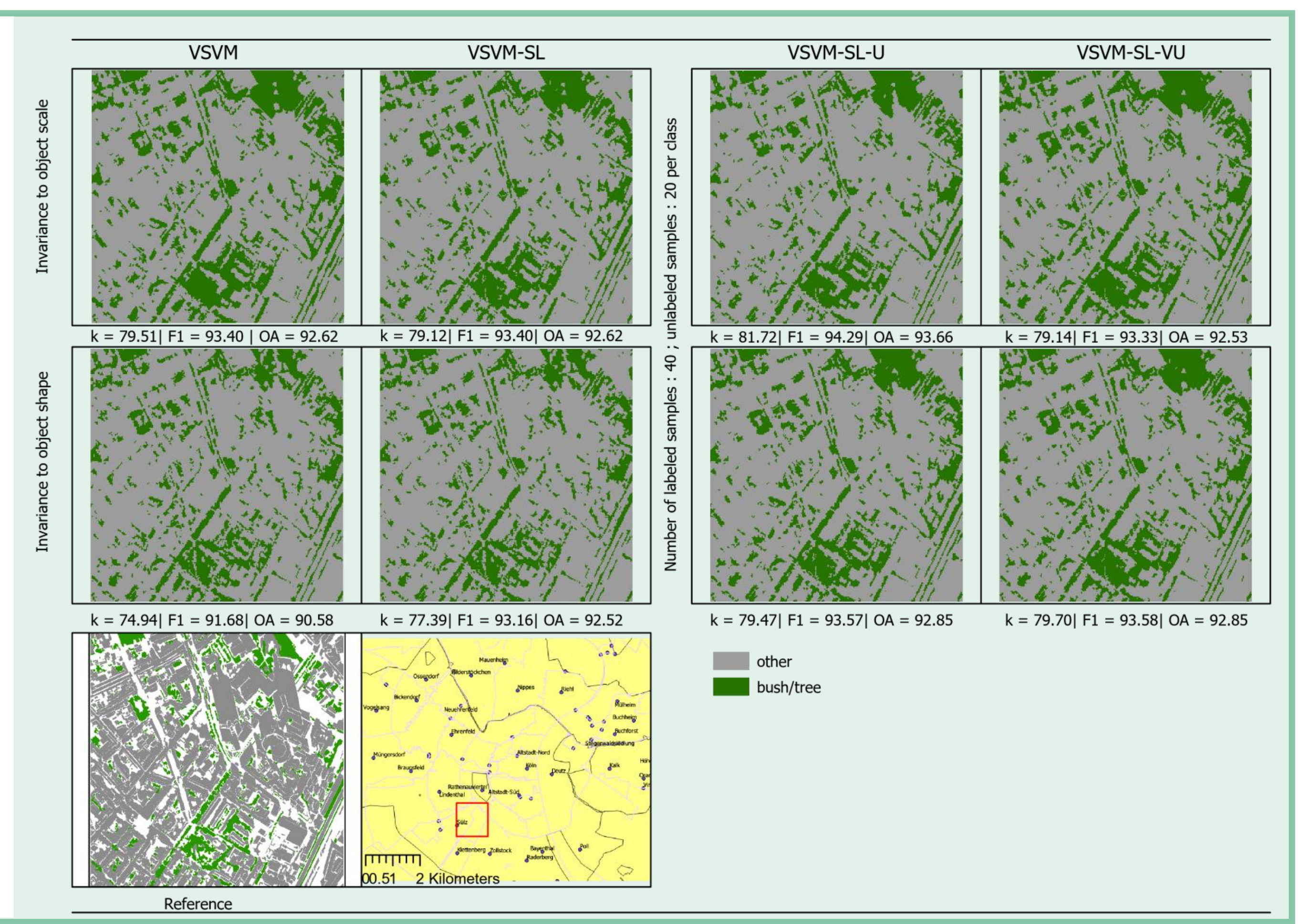


Figure 3: Graph showing the mean accuracy values with 20 realizations for Cologne data set with binary classification settings. Blue colored lines indicate the semi-supervised methods. Figure 4. Visualization of the results from a single realization for binary classification setting for Cologne.

Moreover, a modification of SVM called Virtual Support Vector Machines (VSVM) is used in the thesis to benefit from virtual samples (Fig.1). Self-Learning (SL) strategy is further used to prune these virtual and unlabeled samples. (Fig. 2)

METHODOLOGY

Four new methods are developed for the semi-supervised learning and the active learning approach.

Semi-supervised learning algorithms;

- Algorithm 1: VSVM-SL with unlabeled samples.
- Algorithm 2: VSVM-SL with virtual unlabeled samples
- Algorithm 3: SVM-SL with unlabeled samples.

An active learning approach with uncertainty is developed in order to boost the model with uncertainty visualizations and relabeling the most uncertain samples.

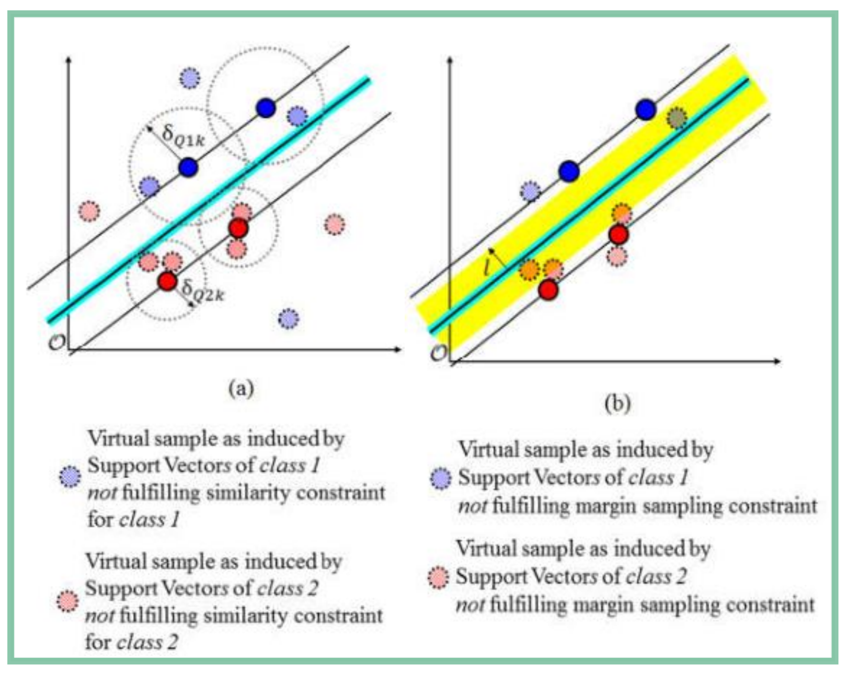


Figure 2: Working principle of SL strategy [2]. a) Virtual samples are pruned with similarity constraints. b) Remaining virtual samples pruned with margin sampling constraint.

RESULTS

In the evaluation of newly proposed semi-supervised algorithms, two different data sets are used with their configurations as invariances of scale and shape of the objects. Data sets were taken from the VHR multispectral imagery acquired by the World View- II sensor for the areas Cologne, Germany, and Hagadera refugee camp, Kenya. All the methodology are evaluated with the mean accuracy and kappa statistics graphs, tables, and visualizations. See in Fig 3 and 4. In the case study of extension on active learning, uncertainty visualizations are generated for the newly developed methods on relabeling most uncertain samples. Lastly, the uncertainty of the new methods is compared. See in Fig 5.

CONCLUSION

Results showed that semi-supervised methods obtained higher accuracies compared to the baseline methods for both of the data sets. Classification maps and tables underlined the improvement of spatial consistency. Consequently, the active learning method showed that relabeling most uncertain samples based on uncertainty visualizations increase the accuracy of developed methods.

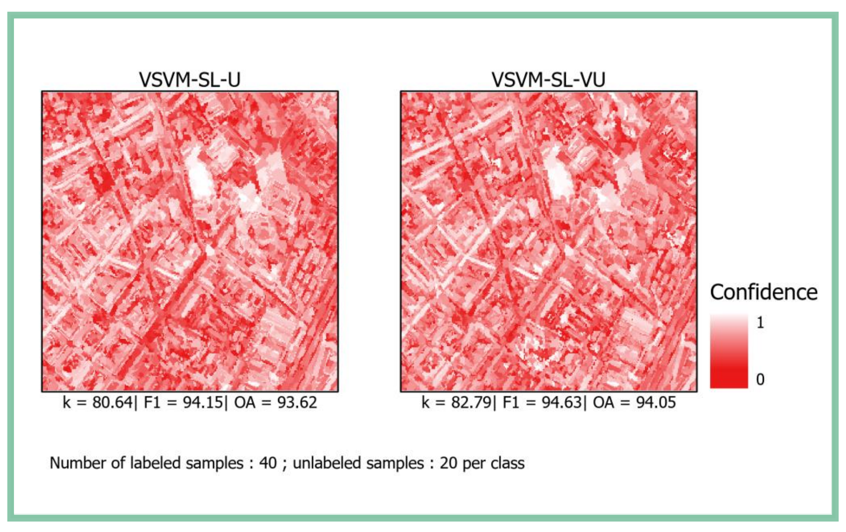


Figure 5: Comparision of uncertainty visualizations for the two semi-supervised methods on Cologne.

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KEYWORDS

classification, support vector machines, self-learning, active learning, uncertainty, visualization, VHR imagery

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