

WIDE CONTEXTUAL RESIDUAL NETWORK WITH ACTIVE LEARNING FOR REMOTE SENSING IMAGE CLASSIFICATION

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Abstract

In this paper, we propose a wide contextual residual network (WCRN) with active learning (AL) for remote sensing image (RSI) classification.

Though ResNets have achieved great success in various applications, its performance is limited by the requirement of abundant labeled samples. As it is very **difficult and expensive to obtain class labels** in real world, we integrate the proposed WCRN with AL to improve its generalization by using the most informative training samples.

Specifically, we first **design a WCRN** for RSI classification, and then **integrate it with AL** to achieve good machine generalization with limited number of training sampling. Experimental results on Pavia University and Flevoland datasets demonstrate that **the proposed WCRN with AL can significantly reduce the needs of samples**.

Index Terms — Residual networks; active learning; remote sensing; classification; hyperspectral image; SAR

Conclusion

> In this study:

1. A wide contextual residual network (WCRN) is designed.
2. We introduce active learning into the proposed WCRN.

> The **advantages** of the proposed approach:

1. WCRN can extract and maintain the abundant spectral feature information, as well as spatial information in the input RSIs.
2. The integration of AL leads to good machine generalization with limited number of training samples by finding the most informative samples.

Methodology

> Wide Contextual Residual Network (WCRN)

The architecture of the proposed WCRN is shown in Figure 1. Inspired by the prior works, we design the proposed WCRN with a multi-scale convolutional layer and one residual unit. In the proposed WCRN, the number of kernels in a convolutional layer is significantly larger than that in the traditional CNN or ResNets.

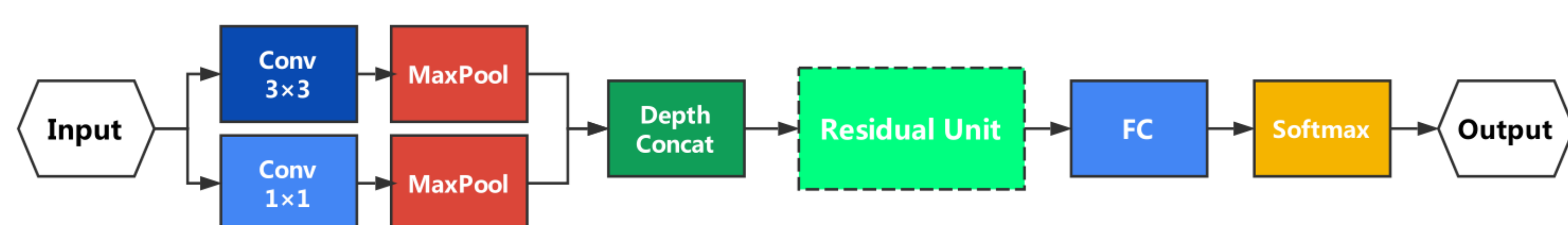


Figure 1. The proposed WCRN

> Data Augmentation and Voting

1. To avoid overfitting, training samples are augmented.
2. In order to increase the model stability, in the end of AL, models of the final nine epochs are used to predict a group of results, while the final results are generated by majority voting.

> Active Learning

A relevant question for AL is what samples in the unlabeled set are informative and should be chosen for training. Base on the posterior probabilities produced by the proposed networks, we adopt four different sampling schemes (**RS, MI, BT and MBT**) for selection.

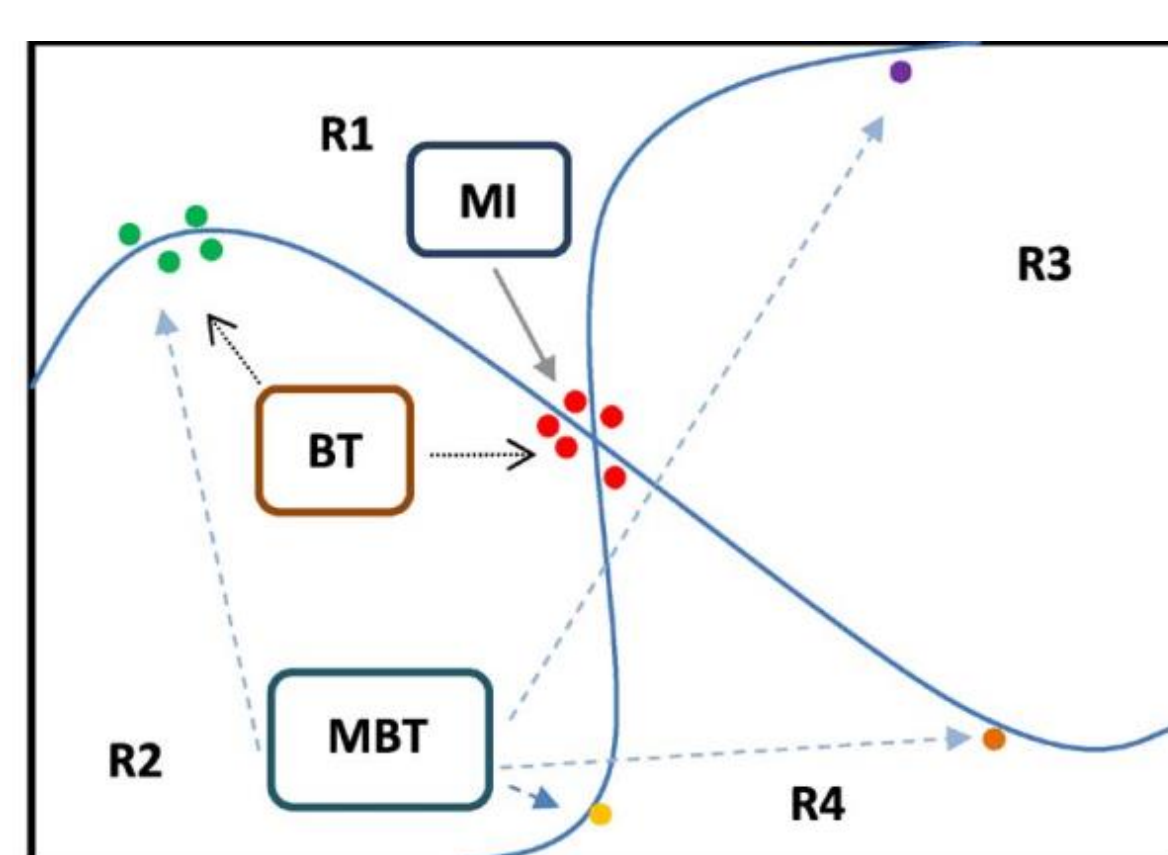


Figure 2. Graphical illustration of AL approaches in a toy example.

Result

> Experiment in the Pavia University Dataset:

No. of Residual Units	No. of Kernels	OA
1	32	97.69 ± 0.21 %
1	64	98.07 ± 0.20 %
1	128	98.28 ± 0.25 %
1	256	98.36 ± 0.26 %
2	32	97.88 ± 0.36 %
2	64	98.13 ± 0.37 %
2	128	98.24 ± 0.20 %
2	256	98.27 ± 0.72 %

Table 1. The OAs, along with the standard deviations, obtained by the proposed WCRN by using different number of residual units and kernels.

Method	OA	Samples
Contextual CNN [6]	95.97 ± 0.46 %	1800
Contextual CNN (vote)	97.75 ± 0.24 %	1800
WCRN	98.36 ± 0.26 %	1800
Contextual CNN (vote)	94.06 ± 1.19 %	600
WCRN (RS)	96.22 ± 0.38 %	600
WCRN (MI)	99.41 ± 0.09 %	600
WCRN (BT)	99.43 ± 0.08 %	600
WCRN (MBT)	99.31 ± 0.08 %	600

Table 2. The obtained overall accuracies(OAs, averaging from 10 independent runs), along with standard deviations for the UP dataset).

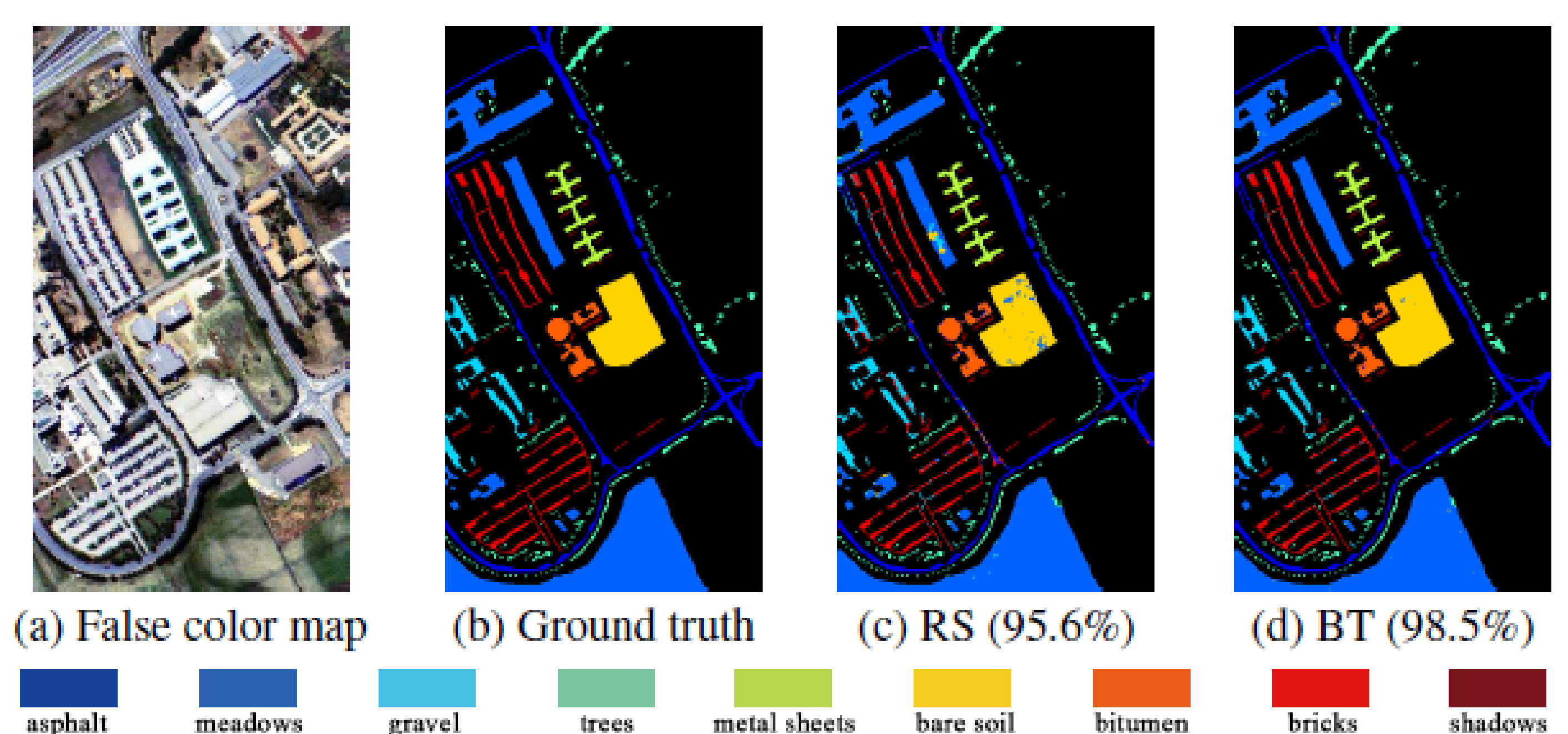


Figure 2. The classification maps, along with the OAs of the UP dataset.

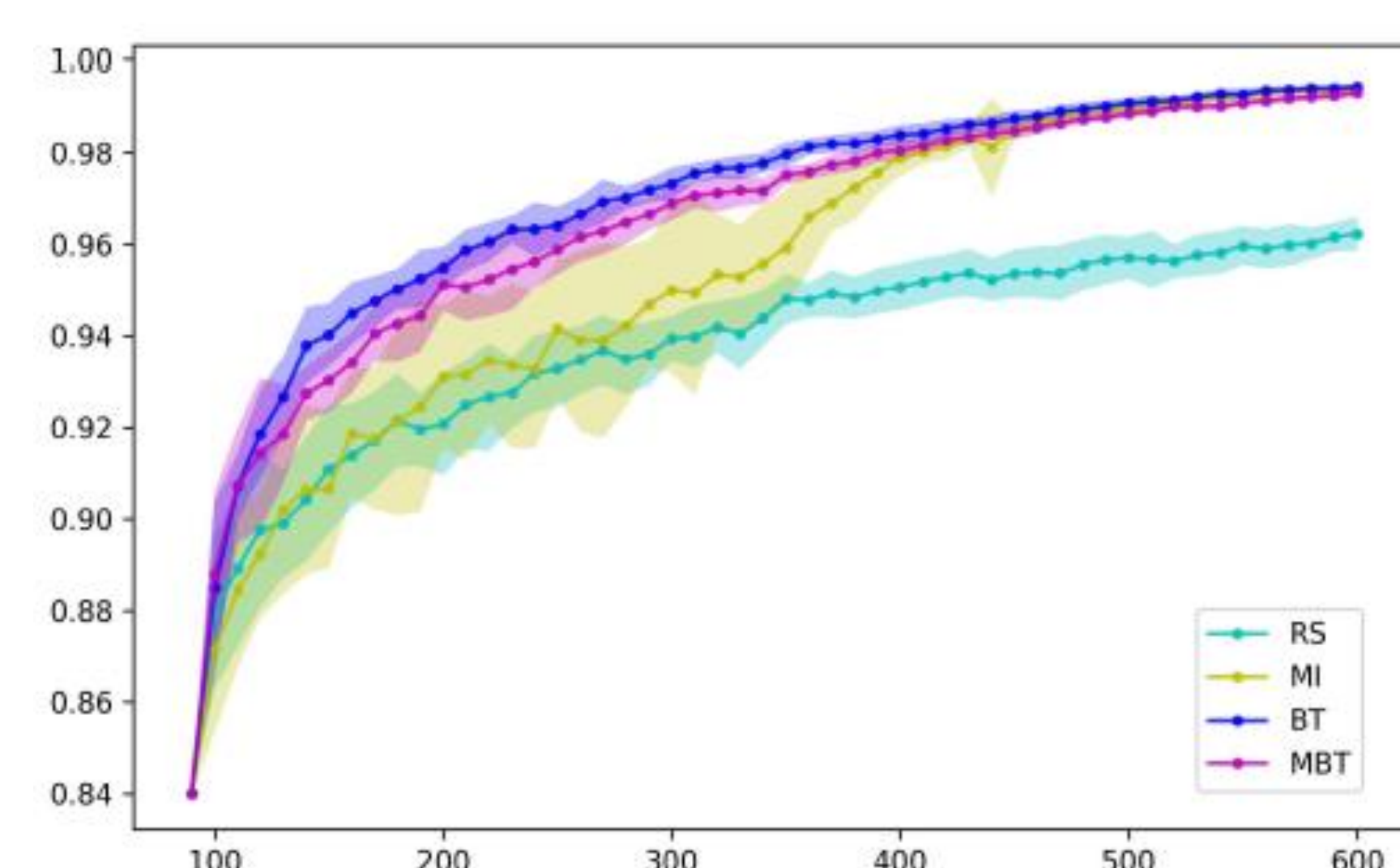


Figure 3. The OAs, along with the standard deviations, as a function of the number of training samples in the AL scheme of WCRN over the UP dataset.

We conducted another experience in the Flevoland dataset, and obtained a similar result.