Creating Classifier Ensembles through Meta-heuristic Algorithms for Aerial Scene Classification

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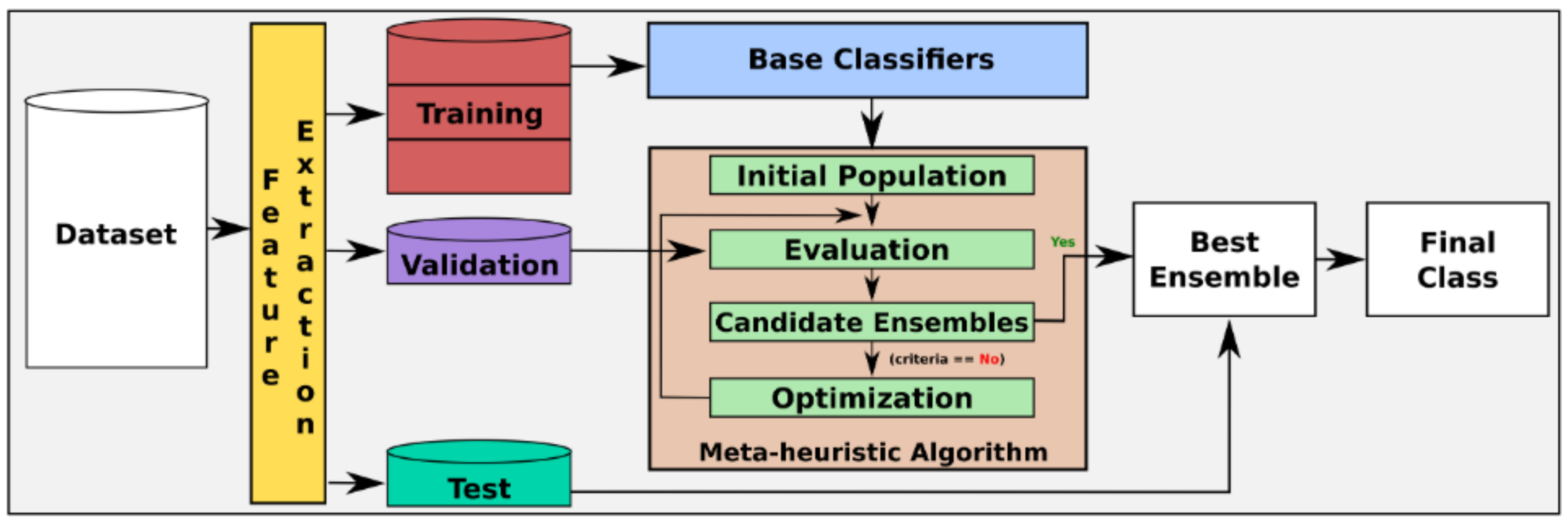
Abstract

Convolutional Neural Networks (CNN) have been being widely employed to solve the challenging remote sensing task of aerial scene classification. Nevertheless, it is not straightforward to find single CNN models that can solve all aerial scene classification tasks, allowing the development of a better alternative, which is to fuse CNN-based classifiers into an ensemble. However, an appropriate choice of the classifiers that will belong to the ensemble is a critical factor, as it is unfeasible to employ all the possible classifiers in the literature. Therefore, this work proposes a novel framework based on meta-heuristic optimization for creating optimized ensembles in the context of aerial scene classification. The experimental results were performed across nine meta-heuristic algorithms and three aerial scene literature datasets, being compared in terms of effectiveness (accuracy), efficiency (execution time), and behavioral performance in different scenarios. Our results suggest that the Univariate Marginal Distribution Algorithm shows more effective and efficient results than other commonly used meta-heuristic algorithms, such as Genetic Programming and Particle Swarm Optimization.

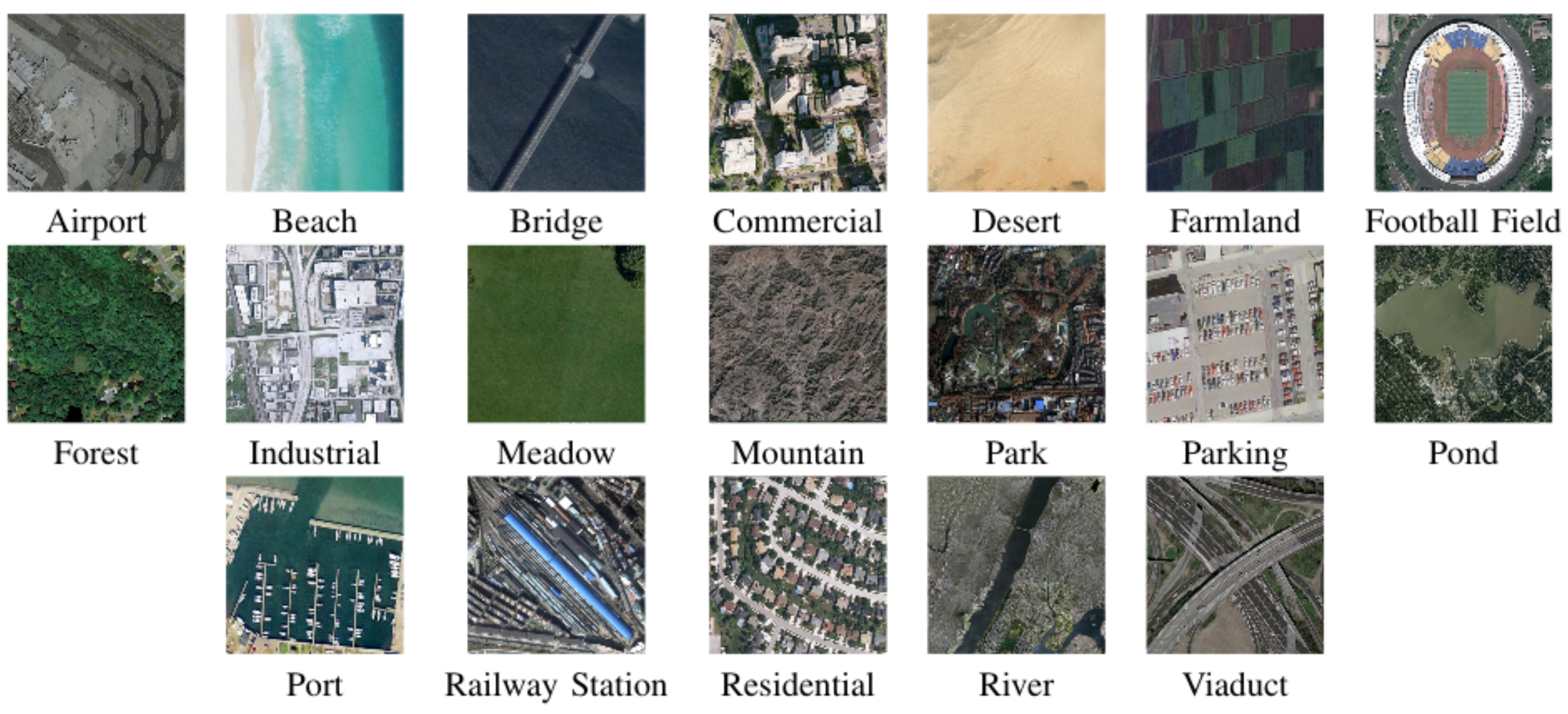
Framework for Building Classifier Ensemble



Experimental Setup

- **Three datasets:**

Dataset	Classes	Images per Class (Total)	Dimension	Spatial Resolution
RSSCN7	7	400 (2,800)	400×400	–
UCMerced	21	100 (2,100)	256×256	0.3m
WHU-RS19	19	50–61 (1,005)	600×600	up to 0.5m



- **Learning Methods:** We used six learning methods in the framework: Naıve Bayes (NB), Decision Tree (DT), Naıve Bayes (NB), Support Vector Machine (SVM), and k-Nearest Neighborhood (kNN) using k ={1,3,5,7}. All implementations in the WEKA.
- **Deep Learning Features:** VGG16,VGG19, Inception-v3, Xception, and Resnet-50.
- **Global Descriptors:** BIC, CCV, GCH, QCCH, and LAS.
- **Baseline:** Majority Voting.
- **Evaluation Measure:** Accuracy, number of used classifiers, and time.
- **Experimental protocol:** 5-fold cross-validation protocol and all results are reported in terms of the average among five runs.

Experiments

- In this work, we have performed three different experiments:

(1) is a comparative study among nine different optimization algorithm using three different scenarios (Global, CNN, and ALL) and three well-known aerial scene datasets (WHU-RS19, RSSCN7, and UCMerced);

(2) is a comparative analysis of the number of base classifiers present in the final ensembles built by optimization algorithms; and

(3) an efficiency analysis among the nine algorithms used in the optimization process.

Classification Results

WHU-RS19 dataset

Algs.	WHU-RS19					
	Global (35)	#	CNN (35)	#	ALL (70)	#
ABC	76.5 (±3.0)	16	95.8 (±1.0)	17	94.5 (±1.8)	32
BA	76.8 (±3.0)	18	95.6 (±1.0)	17	93.9 (±1.5)	30
BHA	76.5 (±3.0)	16	95.8 (±1.0)	15	94.4 (±1.3)	33
CS	78.2 (±3.0)	17	95.7 (±1.0)	16	95.6 (±1.4)	25
FA	76.5 (±3.0)	18	95.2 (±2.0)	17	94.6 (±1.7)	35
FPA	77.6 (±3.0)	15	96.6 (±1.0)	14	95.3 (±1.0)	33
GP	77.2 (±3.0)	26	95.1 (±2.0)	12	93.6 (±1.6)	25
PSO	75.9 (±3.0)	18	95.7 (±1.0)	14	94.1 (±2.0)	31
UDMA	76.8 (±2.8)	19	96.9 (±1.0)	14	96.0 (±1.5)	30
Average	76.7	20	95.7	17	94.5	34
Baseline (MV)	75.4 (±3.0)	35	94.2 (±1.0)	35	93.4 (±1.5)	70
Gain (Best × MV)	2.8	-20	2.7	-23	2.6	-45

RSSCN7 dataset

Algs.	RSSCN7					
	Global (35)	#	CNN (35)	#	ALL (70)	#
ABC	81.8 (±1.0)	18	90.3 (±0.0)	17	90.7 (±0.6)	35
BA	81.5 (±1.0)	20	90.4 (±1.0)	18	90.3 (±0.7)	36
BHA	81.9 (±1.0)	19	90.4 (±1.0)	16	90.2 (±0.6)	32
CS	81.5 (±2.0)	21	90.6 (±1.0)	14	90.9 (±0.9)	32
FA	81.3 (±2.0)	19	90.1 (±1.0)	18	90.0 (±0.8)	38
FPA	81.3 (±2.0)	18	90.7 (±1.0)	16	90.7 (±1.2)	35
GP	81.0 (±2.0)	27	89.6 (±1.0)	17	90.3 (±0.9)	44
PSO	81.5 (±1.0)	18	90.4 (±1.0)	18	90.4 (±0.8)	35
UDMA	81.9 (±1.1)	21	90.9 (±1.0)	16	91.1 (±0.4)	32
Average	81.6	22	90.3	19	90.4	39
Baseline (MV)	81.8 (±1.0)	35	89.5 (±1.0)	35	89.8 (±0.9)	70
Gain (Best × MV)	0.1	-17	1.4	-21	1.3	-38

UCMerced dataset

Algs.	UCMerced					
	Global (35)	#	CNN (35)	#	ALL (70)	#
ABC	79.0 (±1.0)	18	94.2 (±1.0)	16	94.1 (±1.5)	34
BA	78.9 (±1.0)	20	94.0 (±1.0)	17	93.6 (±0.9)	36
BHA	78.9 (±1.0)	19	94.9 (±0.0)	16	93.6 (±1.3)	38
CS	79.9 (±1.0)	20	94.8 (±1.0)	13	94.1 (±1.2)	30
FA	79.0 (±1.0)	21	93.9 (±1.0)	16	92.9 (±1.5)	37
FPA	79.7 (±2.0)	19	94.3 (±1.0)	16	94.1 (±1.1)	31
GP	78.9 (±1.0)	25	94.0 (±2.0)	15	93.6 (±1.6)	41
PSO	79.6 (±1.0)	20	94.0 (±1.0)	16	93.3 (±0.8)	36
UDMA	79.9 (±0.7)	20	94.7 (±1.0)	15	94.4 (±1.4)	29
Average	79.3	22	94.2	18	93.6	38
Baseline (MV)	78.9 (±1.0)	35	93.5 (±1.0)	35	92.6 (±1.7)	70
Gain (Best × MV)	1.0	-17	1.2	-22	1.8	-41

Efficiency Results

Algorithms	Time(s)					
	WHU-RS19	@R	RSSCN7	@R	UCMerced	@R
ABC	532 (±16)	9°	2946 (±95)	9°	2150 ±70)	9°
BA	371 (±5)	7°	1944 (±102)	7°	1580 ±107)	7°
BHA	366 (±11)	6°	1908 (±88)	5°	1494 ±53)	5°
CS	520 (±12)	8°	2865 (±84)	8°	2264 ±87)	8°
FA	181 (±10)	2°	924 (±51)	2°	655 ±53)	2°
FPA	347 (±12)	5°	1924 (±65)	6°	1525 ±22)	6°
GP	182 (±9)	3°	1041 (±52)	4°	660 ±47)	3°
PSO	182 (±9)	4°	939 (±73)	3°	661 ±54)	4°
UDMA	132 (±29)	1°	292 (±31)	1°	208 ±51)	1°

Conclusions

- All meta-heurisc algorithms achieved better classification results than baseline (MV);
- Optimization algorithms reduced the number of classifiers in the final ensembles by at least **49%;**
- **UDMA** algorithm is at least **~1.4x** faster than the most efficient optimization algorithm compared in this work;
- **Code is available on https://github.com/gugarosa/evolutionary_ensembles**

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