SS-MLA: A Novel Solution for Multi-Label Classification of Remotely Sensed Images

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Thank you for your valuable contributions in advance.

Source: https://github.com/Hua-YS/AID-Multilabel-

Agenda

SS-MLA

- Problem Definition
- Annotating Remotely Sensed Images by Transfer Learning (ARSI-TL)
- Semi-Supervised Multi-Label Annotizer (SS-MLA)
- Comparison of ARSI-TL and SS-MLA
- Summary of References

Important Remarks

- The logical connectivity between proposed methods.
- Motivations and contributions.
- Statistical properties of datasets and their relation with the results.
- Granularity of labeling.

Problem Definition (Informal)

- Assigning multiple labels to remotely sensed images is made possible by *setting up relationships between specific image features and individual labels.*
- If multiple mapped image features are found in a given im ultiple labels are assigned to t ge.

Trees, pavement, building, ...

Problem Definition (Formal)

- Assume that D is the matrix of training data. Then, a machine learning method can be defined as follows:

$$F : D \rightarrow Y$$

- Where Y is a multihot encoded array of binary vectors. For each relevant label of each image, there is a 1 in the respected column of the label in Y.

Datasets: DFC15 Multi-Label

Table 2.1: The distribution of labels in each class for the DFC15 Multi-Label.

Class No.	Class Name	Total
1	Impervious	3133
2	Water	998
3	Clutter	1891
4	Vegetation	1086
5	Building	1001
6	Tree	258
7	Boat	270
8	Car	705
-	All	3342

Datasets: AID and UCM Multi-Label Datasets

Table 2.2: The distribution of labels in each class for the UCM Multi-Label and AID Multi-Label datasets.

Class No.	Class Name	Total	
		UCM Multi-Label	AID Multi-Label
1	bare soil	718	1475
2	airplane	100	99
3	building	691	2161
4	car	886	2026
5	chaparral	115	112
6	court	105	344
7	dock	100	271
8	field	104	214
9	grass	975	2295
10	mobile-home	102	2
11	pavement	1300	2328
12	sand	294	259
13	sea	100	221
14	ship	102	284
15	tank	100	108
16	tree	1009	2406
17	water	203	852
-	All	2100	3000

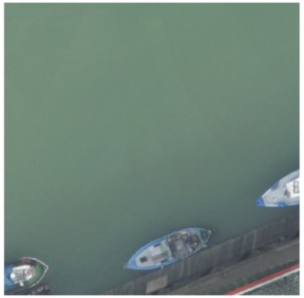
Datasets: Ankara Dataset

Table 2.3: The image distribution across labels for Ankara Dataset.

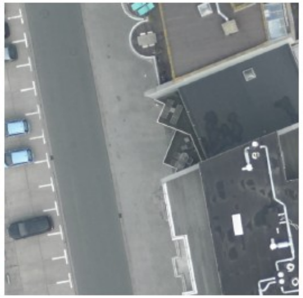
Class No.	Class Name	Total	Class No.	Class Name	Total
1	Grass Covered Soil	215	16	Blue Roofing	25
2	Bare Soil	216	17	Yellow Roofing	13
3	Arid Soil	10	18	Membrane Roofing	57
4	Rocky	31	19	Concrete Roofing	55
5	Tree	174	20	White Tent	6
6	Reeds	5	21	Unpaved Road	106
7	Crop (Type-A)	47	22	Asphalt Pavement	183
8	Crop (Type-B)	38	23	Highway Pavement	12
9	Crop (Type-C)	2	24	Grass (Type-A)	215
10	Crop (Type-D)	55	25	Grass (Type-B)	12
11	Crop (Type-E)	4	26	Grass (Type-C)	25
12	Red Roofing	131	27	Lake	11
13	Metal Roofing	130	28	Pool	23
14	White Roofing	122	29	Cloud	6
15	Green Roofing	41	-	All	216

Datasets: Summary

(a) *Impervious, water, clutter, building.*



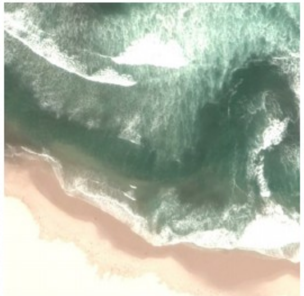
(b) *Impervious, water, building, boat.*



(c) *Impervious, building, car.*

(d) *Impervious, water, vegetation.*

(e) *Airplane, bare-soil, buildings, cars, grass, pavement, trees.*



(f) *Sand, sea.*

(g) *Bare-soil, field, grass, trees, water.*

(h) *Bare-soil, buildings, grass, pavement, tanks, trees, water.*

Datasets: Summary

Table 3.1: Remotely sensed multi-label image classification datasets.

Properties \ Dataset Name	AID Multi-Label	UCM Multi-Label	DFC15 Multi-Label	Ankara Dataset
Image Size	600×600	256×256	600×600	63×63
# of Images	3000	2100	3342	216
# of Distinct Labels	17	17	8	29
DLS	297	202	65	127
PDLS	0.0990	0.0962	0.0194	0.5880
LC	5.1523	3.3348	2.7953	9.1204
LD	0.3031	0.1962	0.3494	0.3145

Our Proposed Solutions: ARSI-TL

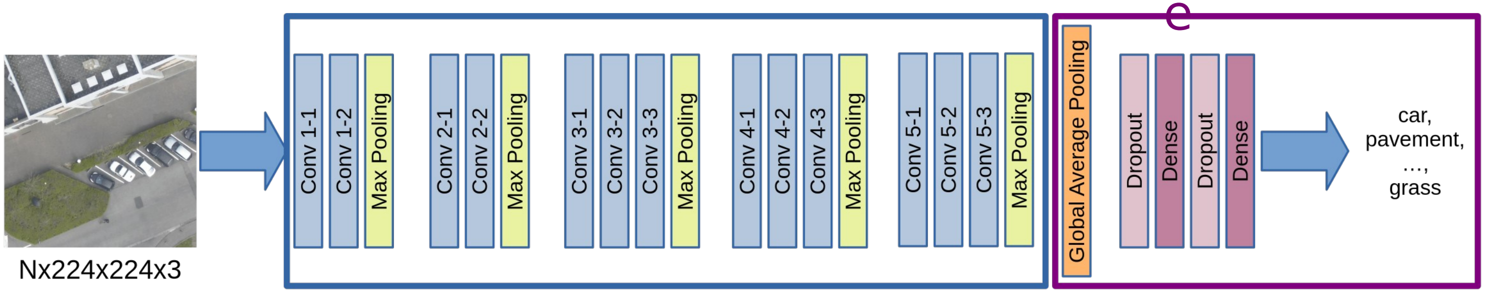
- Motivation
  - Label relation information in small and imbalanced datasets may not be as effective as with larger datasets.
  - To test this hypothesis, a straightforward CNN-based model is developed.

Our Proposed Solutions: ARSI-TL (cont'd)

- There are two subnetworks in the proposed model:
  - A pre-trained VGG16 for image feature extraction (as shown in blue box).
  - A fully-connected dense layer form feature classification (as shown in purple box).

Non-Trainable

Trainabl
e



VGG16
Feature Extraction with Transfer Learning

Multi-Label Prediction

Our Proposed Solutions: ARSI-TL (cont'd)

Table 3.2: Comparison of the proposed model on the AID Multi-Label dataset.

Method Name	Results of Published Methods				Results of Proposed Method				Testing Method
	P	R	F_1	F_2	P	R	F_1	F_2	
GRN-SNDL-BCE [7]	92.79	91.08	**90.95**	90.82	90.18 ± 0.23	88.89 ± 0.19	$\mathbf{88.23 \pm 0.16}$	88.31 ± 0.16	Random Split[1]
Zhu et al. [11]	89.72	88.41	87.49	-	87.62 ± 0.93	88.46 ± 0.65	86.46 ± 0.70	87.12 ± 0.66	Random Split[2]
AL-RN-ResNet [9]	91.00	88.95	88.72	88.54					

[1] 70% train, 20% test, 10% validation
[2] 80% train, 10% test, 10% validation

Table 3.3: Comparison of the proposed model on the UCM Multi-Label dataset.

Method Name	Results of Published Methods				Results of Proposed Method				Testing Method
	P	R	F_1	F_2	P	R	F_1	F_2	
GRN-SNDL-BCE [7]	91.98	92.83	91.31	91.92	88.22 ± 0.62	88.85 ± 0.69	87.22 ± 0.48	87.84 ± 0.57	Random Split[1]
Zhu et al. [11]	91.75	91.65	90.62	-	88.57 ± 0.80	89.36 ± 0.69	$\mathbf{87.84 \pm 0.64}$	88.44 ± 0.64	Random Split[2]
AL-RN-ResNet [9]	88.81	87.07	86.76	86.67					
CA-ResNet-BiLSTM [6]	77.94	89.02	81.74	85.27					
LR-ResNet [10]	87.10	85.80	85.30	-					

[1] 70% train, 20% test, 10% validation
[2] 80% train, 10% test, 10% validation

Our Proposed Solutions: ARSI-TL (cont'd)

Table 3.4: Comparison of the proposed model on DFC15 Multi-label Dataset.

Method Name	Results of Published Methods				Results of Proposed Method				Testing Method
	P	R	F_1	F_2	P	R	F_1	F_2	
GRN-SNDL-BCE [7]	96.53	95.95	**95.80**	95.78	95.37 ± 0.18	93.07 ± 0.27	93.42 ± 0.24	93.04 ± 0.26	Random Split[1]
CA-ResNet-BiLSTM [6]	91.93	79.12	83.65	80.61	95.83 ± 0.34	93.53 ± 0.46	**93.97 ± 0.36**	93.55 ± 0.42	Random Split[2]

[1] 70% train, 20% test, 10% validation
[2] 80% train, 10% test, 10% validation

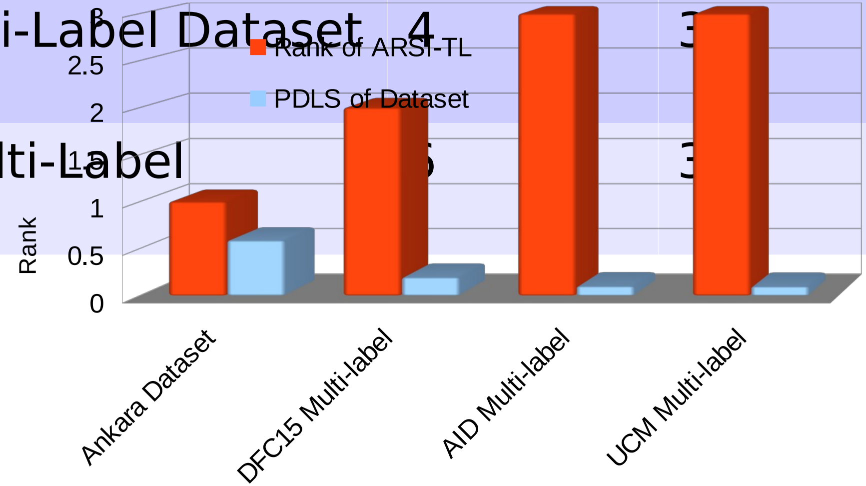
Table 3.5: Comparison of the proposed model on Ankara Dataset.

Method Name	Results of Published Methods				Results of Proposed Method				Testing Method
	P	R	F_1	F_2	P	R	F_1	F_2	
Zhu et al. [11]	81.22	82.12	**76.60**	-	88.30 ± 1.68	82.61 ± 1.98	**84.19 ± 1.58**	82.94 ± 1.58	Random Split[1]

[1] 80% train, 10% test, 10% validation

Our Proposed Solutions: ARSI-TL (cont'd)

Dataset Name	#Methods	ARSI-TL	PDLS
Ankara Dataset	2	1	0.5880
DFC15 Multi-Label Dataset	3	2	0.0194
AID Multi-Label Dataset	4	3	0.0990
UCM Multi-Label Dataset	[illegible]	3	0.0962



Our Proposed Solutions: SS-MLA

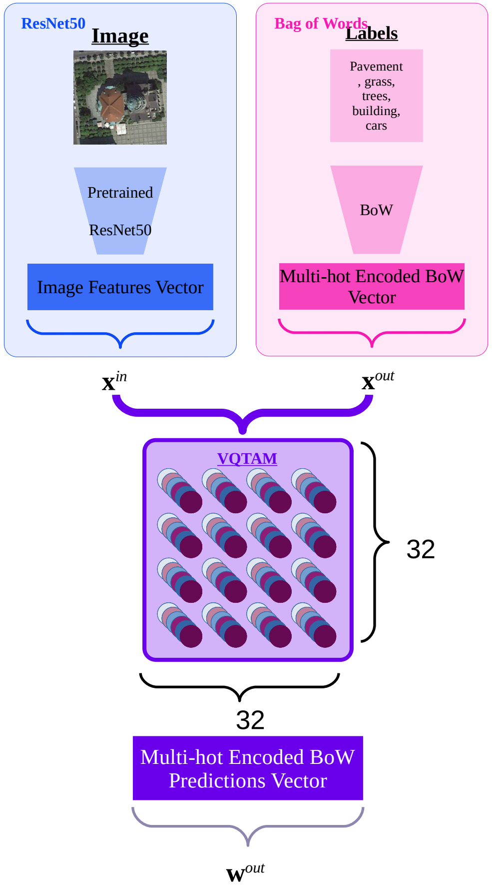
- Motivation
  - Learning from small and imbalanced datasets might be a challenging task for advanced models.
  - It is hard to find large and labeled datasets.
  - An efficient method is needed that both learns from small labeled datasets and able to extend its knowledge from large unlabeled datasets.

Our Proposed Solutions: SS-MLA

Semi-Supervised Multi-Label Annotizer (SS-MLA):

- **Vector Quantized Temporal Associative Memory (VQTAM)**
- VQTAM & SOM **unsupervised**
- SS-MLA:
  - target labels **supervised**, clustering **unsupervised** in the learning process.
  - **semi-supervised** method.

Our Proposed Solutions: SS-MLA (cont’d)



Our Proposed Solutions: SS-MLA (cont’d)

Table 4.2: Comparison of SS-MLA with literature on AID Multi-label Dataset.

Method Name	Results of Published Methods				Results of SS-MLA				Testing Method
	P	R	F_1	F_2	P	R	F_1	F_2	
GRN-SNDL-BCE [7]	92.79	91.08	**90.95**	90.82	91.36 ± 0.48	90.48 ± 0.63	89.70 ± 0.16	89.87 ± 0.42	Random Split[2]
Proposed Model[1]	90.18	88.89	88.23	88.31					
Zhu et al. [11]	89.72	88.41	87.49	-	91.21 ± 0.61	91.02 ± 0.70	$\mathbf{89.88 \pm 0.38}$	90.26 ± 0.53	Random Split[3]
AL-RN-ResNet [9]	91.00	88.95	88.72	88.54					

[1] The model proposed in Chapter 3.
[2] 70% train, 20% test, 10% validation.
[3] 80% train, 10% test, 10% validation.

Our Proposed Solutions: SS-MLA (cont'd)

Table 4.3: Comparison of SS-MLA with literature on UCM Multi-label Dataset.

Method Name	Results of Published Methods				Results of SS-MLA				Testing Method
	P	R	F_1	F_2	P	R	F_1	F_2	
GRN-SNDL-BCE [7]	91.98	92.83	**91.31**	91.92	89.23 ± 0.78	92.15 ± 0.87	89.55 ± 0.56	90.78 ± 0.68	Random Split[2]
Proposed Model[1]	88.57	89.36	87.84	88.44	89.37 ± 0.86	92.23 ± 0.87	**89.60 ± 0.51**	90.83 ± 0.64	Random Split[3]
Zhu et al. [11]	91.75	91.65	90.62	-					
AL-RN-ResNet [9]	88.81	87.07	86.76	86.67					
CA-ResNet-BiLSTM [6]	77.94	89.02	81.47	85.27					
LR-ResNet [10]	87.10	85.80	85.30	-					

[1] The model proposed in Chapter 3.
[2] 70% train, 20% test, 10% validation
[3] 80% train, 10% test, 10% validation

Table 4.4: Comparison of SS-MLA with literature on DFC15 Multi-label Dataset.

Method Name	Results of Published Methods				Results of SS-MLA				Testing Method
	P	R	F_1	F_2	P	R	F_1	F_2	
GRN-SNDL-BCE [7]	96.53	95.95	**95.80**	95.78	95.70 ± 0.39	95.31 ± 0.33	94.92 ± 0.25	95.01 ± 0.27	Random Split[2]
Proposed Model[1]	95.83	93.53	93.97	93.55	96.34 ± 0.29	95.18 ± 0.56	**95.20 ± 0.29**	95.06 ± 0.45	Random Split[3]
CA-ResNet-BiLSTM [6]	91.93	79.12	83.65	80.61					

[1] The model proposed in Chapter 3.
[2] 70% train, 20% test, 10% validation
[3] 80% train, 10% test, 10% validation

Our Proposed Solutions: SS-MLA (cont'd)

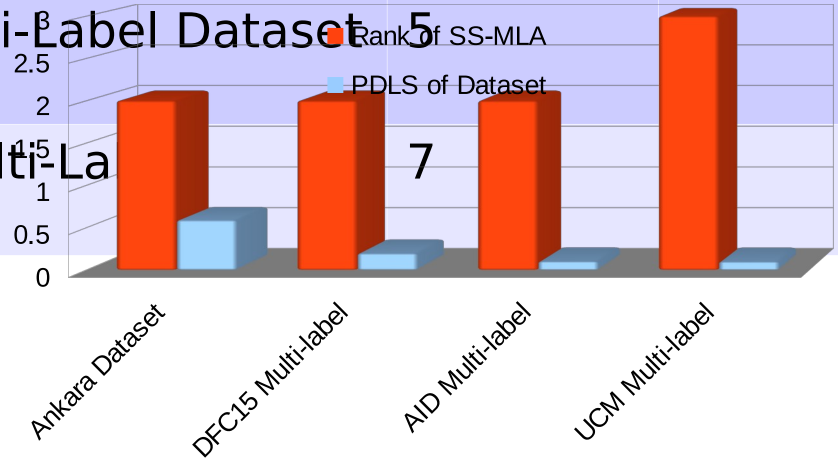
Table 4.5: Comparison of SS-MLA with literature on Ankara Dataset.

Method Name	Results of Published Methods				Results of SS-MLA				Testing Method
	P	R	F_1	F_2	P	R	F_1	F_2	
Proposed Model[1]	88.30	82.61	**84.19**	82.94	85.30 ± 1.81	82.92 ± 1.75	**82.39 ± 1.09**	82.30 ± 1.31	Random Split[1]
Zhu et al. [11]	81.22	82.12	76.60	-					

[1] The model proposed in Chapter 3.
[2] 80% train, 10% test, 10% validation

Our Proposed Solutions: SS-MLA (cont’d)

Dataset Name	#Methods	SS-MLA	PDLS
Ankara Dataset	3	2	0.5880
DFC15 Multi-Label Dataset	4	2	0.0194
AID Multi-Label Dataset	5		0.0990
UCM Multi-La Dataset	7		0.0962



Final Thoughts

- Sophisticated methods may not perform as effective as simpler methods in small, non-diverse, and imbalanced datasets.
- Showed that semi-supervised methods such as SS-MLA can generalize better in small, non-diverse, and imbalancced datasets.
- Several datasets are collected and get together to be able to make a fair comparison and all of the proposed methods are tested and evaluated on multiple datasets.
- To overcome the problem shown in the first bullet, a novel semi-supervised method is introduced to the relevant literature.

Future Work

- This study fouces on multi-label classification of remotely sensed images.
- We will expand the scope of this study to cover the multi-label classification of images other than the remotely sensed ones.
- We will also add the attention mechanism to the expanded version of the proposed method. We expect that the attention mechanism will increase the success of the proposed method.

Summary of References

[1] Zeggada, A., Melgani, F., & Bazi, Y. (2017). A deep learning approach to UAV image multilabeling. IEEE Geoscience and Remote Sensing Letters, 14(5), 694-698.

[2] Hao, Q., Li, S., & Kang, X. (2020). Multilabel sample augmentation-based hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 58(6), 4263-4278.

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[4] Hua, Y., Mou, L., & Zhu, X. X. (2019, May). Multi-label Aerial Image Classification using A Bidirectional Class-wise Attention Network. In 2019 Joint Urban Remote Sensing Event (JURSE) (pp. 1-4). IEEE.

[5] Üstünkök, T., Acar, O. C., & Karakaya, M. (2019, November). Image Tag Refinement with Self Organizing Maps. In 2019 1st International Informatics and Software Engineering Conference (UBMYK) (pp. 1-6). IEEE.

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