A CNN-based Approach For Hyperspectral Images Classification: A Case Study In Wood Fungi Detection

16/09/2021

unibz
Fakultät für Informatik
Facoltà di Scienze e Tecnologie informatiche
Faculty of Computer Science

efre · fesr
Südtirol · Alto Adige
Europäischer Fonds für regionale Entwicklung
Fondo europeo di sviluppo regionale
EUROPEAN UNION
AUTONOME PROVINZ BOZEN SÜDTIROL
PROVINCIA AUTONOMA DI BOLZANO ALTO ADIGE

Outline

Problem statement

Problem solution

Results

Outline

Problem statement

Problem solution

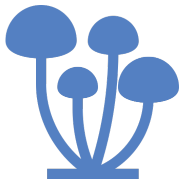
Results

Data description

- 88 labelled Hyperspectral images of wood boards (55 Gb)
- Size: $512 \times y \times 384$, with y ranging from 595 to 962
- 4 classes in total, **clear wood** and 3 classes of fungi: **soft rot**, **brown stain** and **blue stain**

brown stain
soft rot

Wood fungi recognition



Some wood parts are more vulnerable to attacks by fungi

Presence of harmful fungi is often invisible to the human eye

Regular RGB images classification is not enough

Wood fungi recognition

Some wood parts are more vulnerable to attacks by fungi

Presence of harmful fungi is often invisible to the human eye

Regular RGB images classification is not enough

Acquisition and classification of hyperspectral images of wood is necessary

Automatic and early detection of harmful fungi brings economic benefits

Classification problem

- High number of spectral features in HS images

Useful and relevant information

High level of complexity, training computational problems

- How is this problem addressed in the literature?

State of the art

Two major approaches

Two-step technique: feature extraction + classification

PCA + SVM
BOV + SVM
PCA + LR, ...

Deep learning: end-to-end framework

DBNs,
SAEs
CNNs, ...

→ More desirable and at the same time more performing

State of the art

Two major approaches

Two-step technique: feature extraction + classification

PCA + SVM
BOV + SVM
PCA + LR, …

Deep learning: end-to-end framework

DBNs,
SAEs
CNNs, …

→ More desirable and at the same time more performing

In the wood domain

Two-step technique, but HS images classification has never been applied for wood **fungi** detection

What is missing

- ✕ No holistic method that combines spatial and spectral features
- ✕ Few works have exploited CNNs, one of the most promising architecture
- ✕ No study has used HS images for the task of wood fungi detection
- ✕ No end-to-end framework for HS classification in the wood domain

What is missing

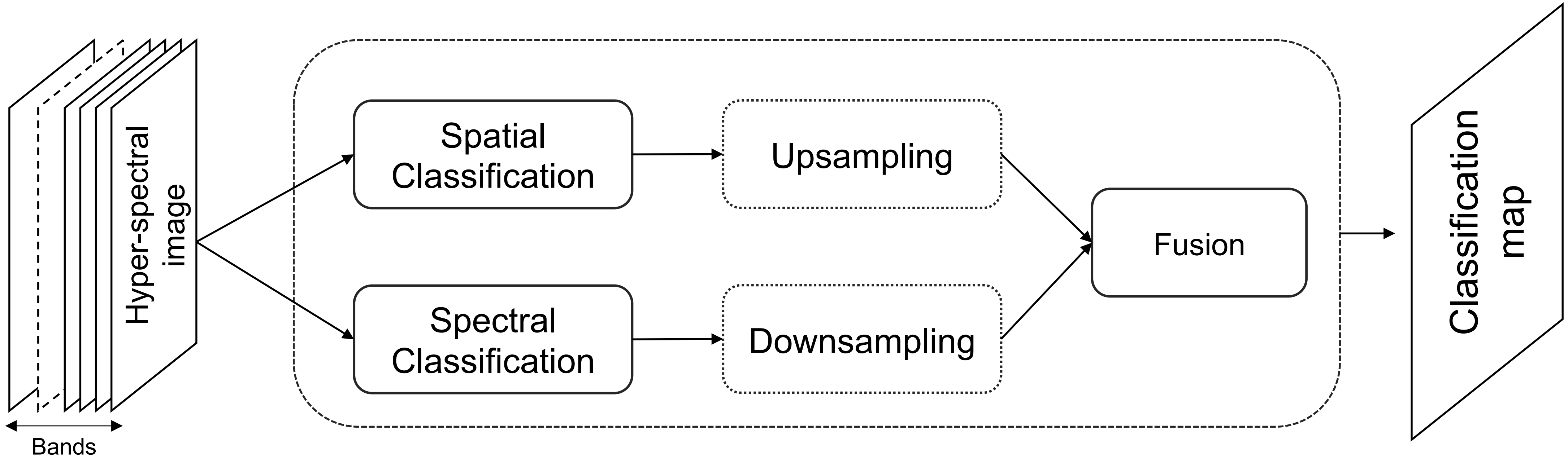
- ✅ No holistic method that combines spatial and spectral features
- ✅ Few works have exploited CNNs, one of the most promising architecture
- ✅ No study has used HS images for the task of wood fungi detection
- ✅ No end-to-end framework for HS classification in the wood domain

What is proposed

CNN-based end-to-end framework for HS images classification, investigating a case study in wood fungi detection

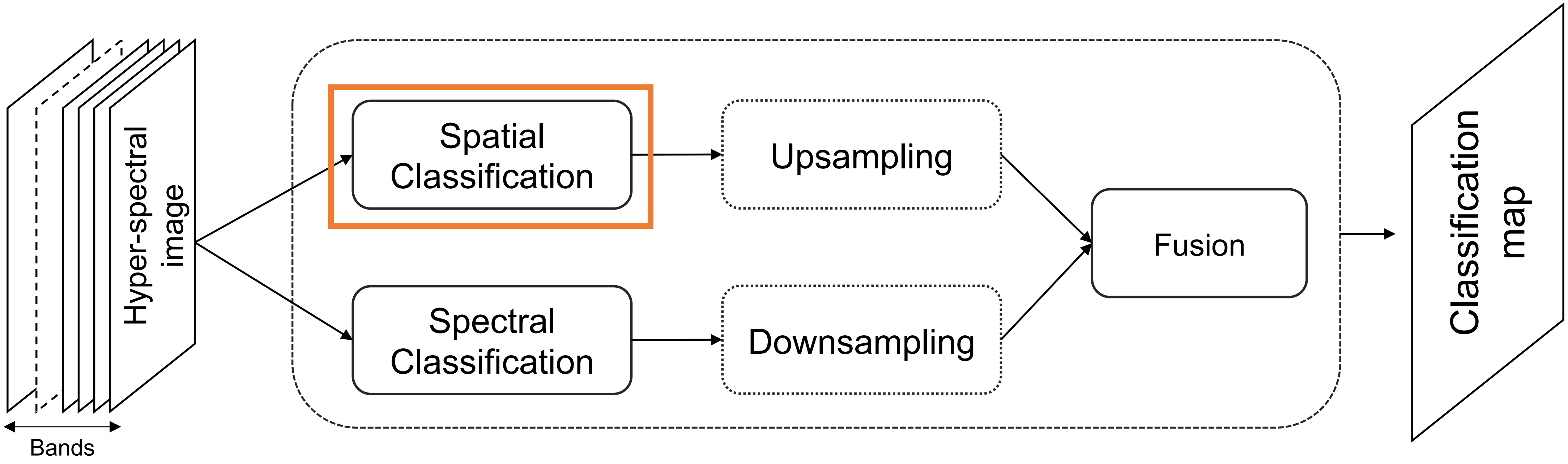
Conceptual framework

- **Input**: Hyperspectral images with *n* bands
- **Output**: Classification map



Conceptual framework

- **Input**: Hyperspectral images with *n* bands
- **Output**: Classification map



Objective

- The goal of the project is to answer the following research questions:

  Is it possible to develop an hyperspectral spatial classifier on the basis of a pre-trained general image classifier?

Objective

- The goal of the project is to answer the following research questions:

1. Is it possible to develop an hyperspectral spatial classifier on the basis of a pre-trained general image classifier?

2. Is the HS spatial classifier able to distinguish between clear wood and wood affected by fungi?

Objective

- The goal of the project is to answer the following research questions:

1. Is it possible to develop an hyperspectral spatial classifier on the basis of a pre-trained general image classifier?
2. Is the HS spatial classifier able to distinguish between clear wood and wood affected by fungi?
3. Is the HS spatial classifier able to recognize the different categories of wood fungi?

Objective

- The goal of the project is to answer the following research questions:

1. Is it possible to develop an hyperspectral spatial classifier on the basis of a pre-trained general image classifier?
2. Is the HS spatial classifier able to distinguish between clear wood and wood affected by fungi?
3. Is the HS spatial classifier able to recognize the different categories of wood fungi?
4. Is it possible to convert an hyperspectral single-block classifier into a multi-block classifier to produce a classification map of any wooden board?

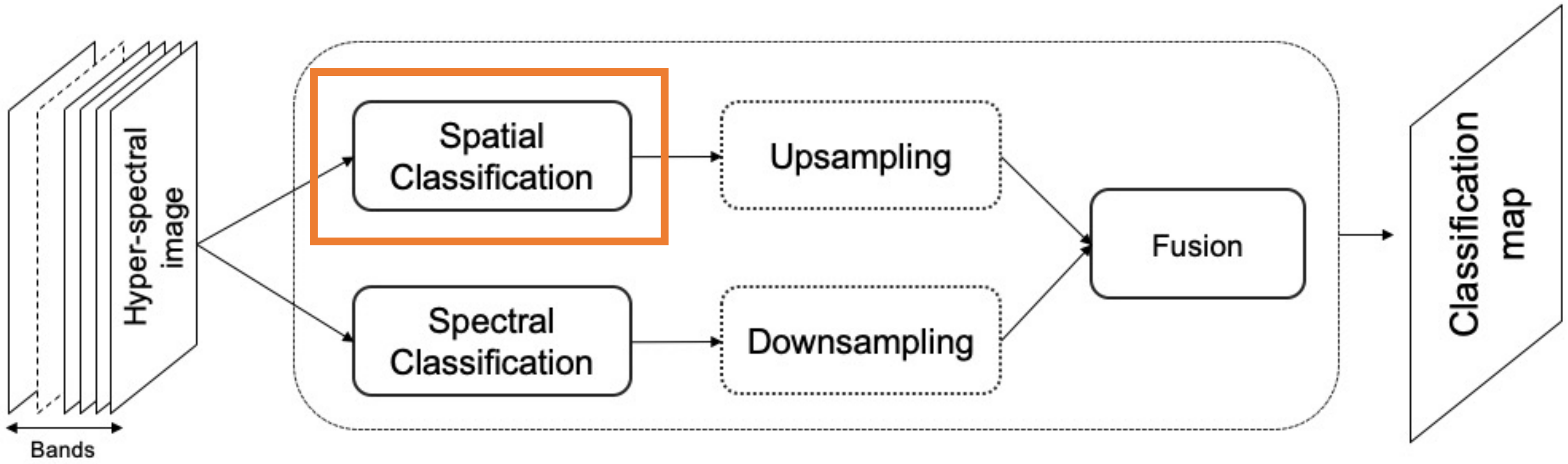
Outline

Problem statement

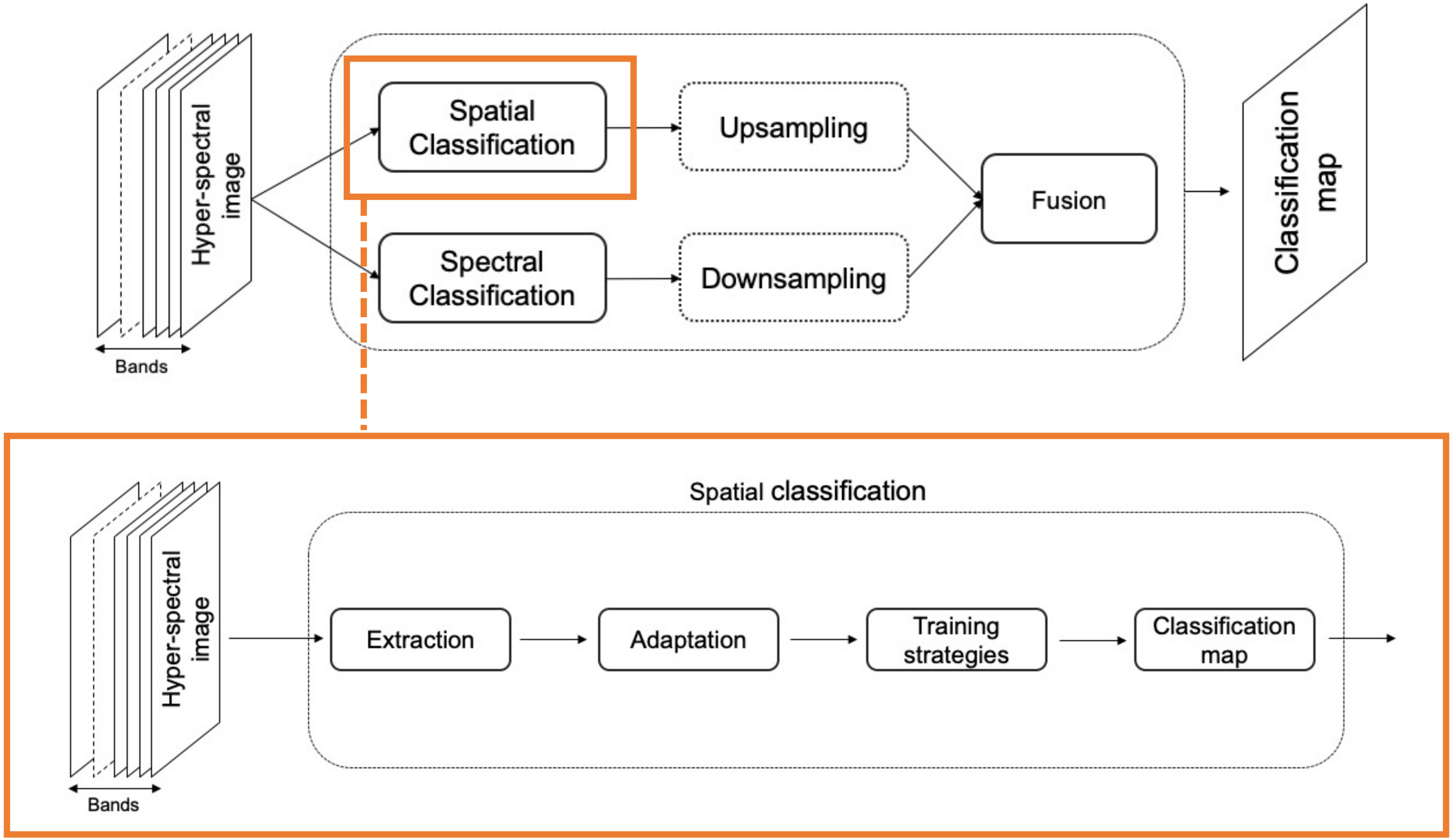
Problem solution

Results

Spatial classification

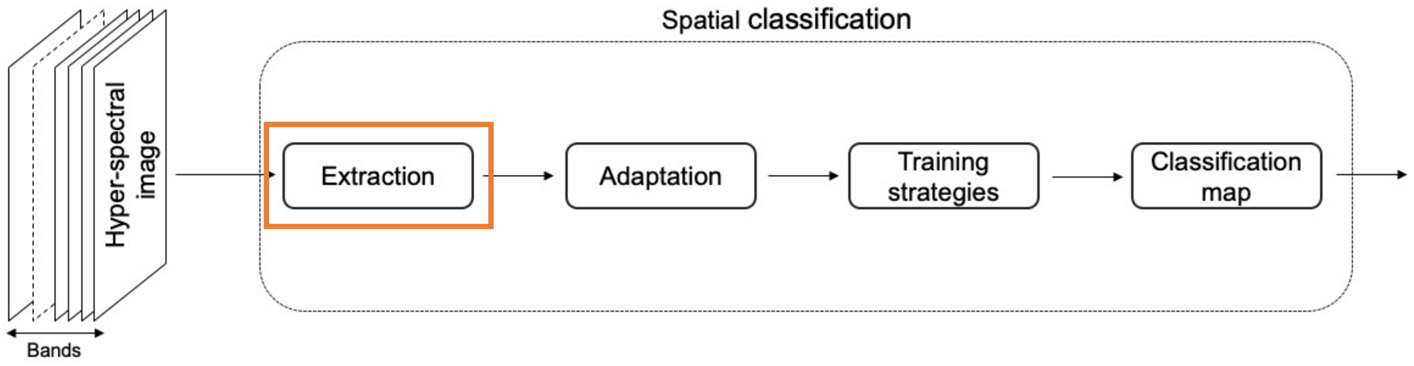


Spatial classification



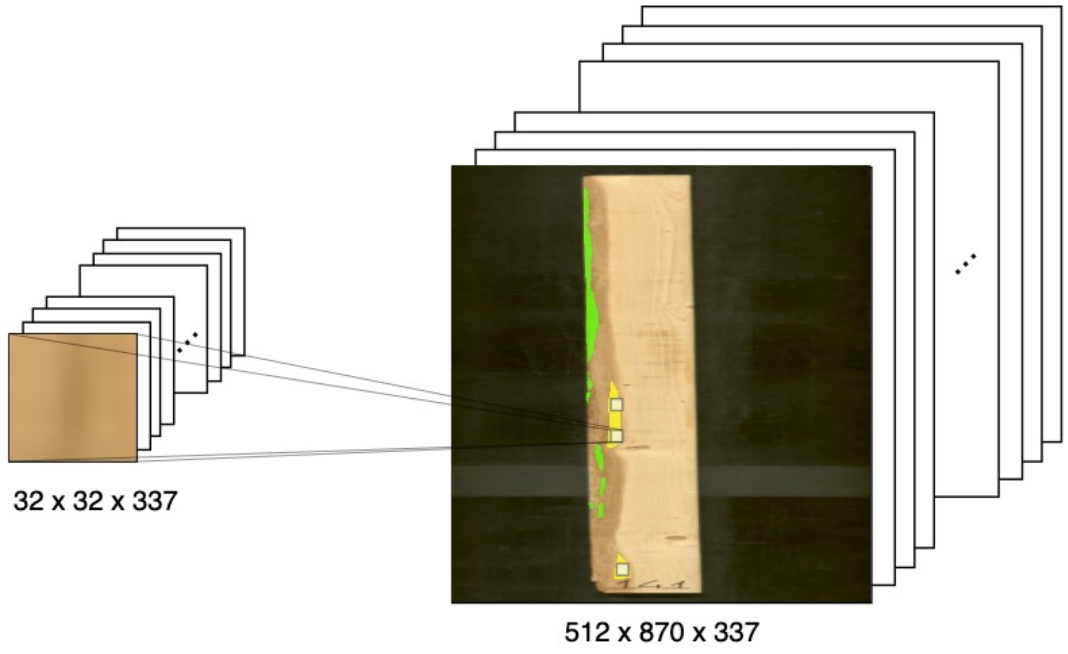
Spatial classification

- **Extraction**
- Adaptation
- Training strategies
- Classification map



Data processing

- **Bands analysis**: reducing bands from 384 to 337, due to non-informative bands
- **Sub-cuboids extraction:** extract $32 \times 32 \times 337$ pure sub-cuboids
- **Train-test split:** 80% training, 20% testing



626 sub-cuboids extracted:

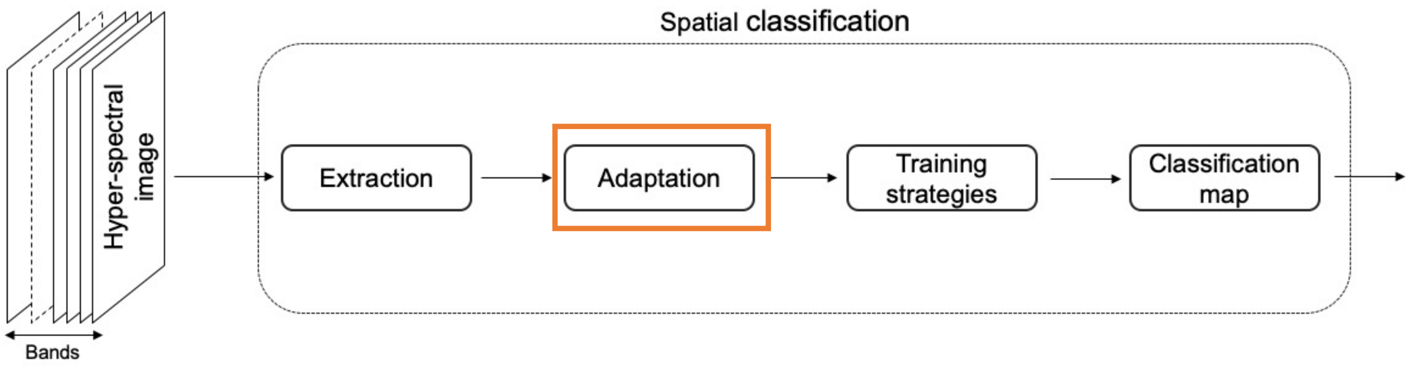
175* clear wood
180 soft rot
171 brown stain
100 blue stain

500 Train

126 Test

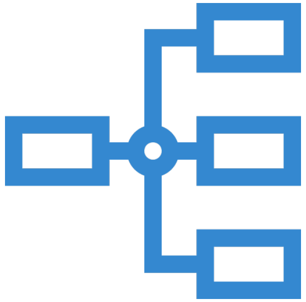
Spatial classification

- Extraction
- **Adaptation**
- Training strategies
- Classification map



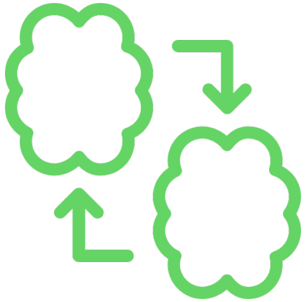
Adaptation process

- The adaptation of a generic image classifier involves two phases



Architectural adaptation

handle the input of multitude spectral bands (337) and the classification among the categories into consideration (4)



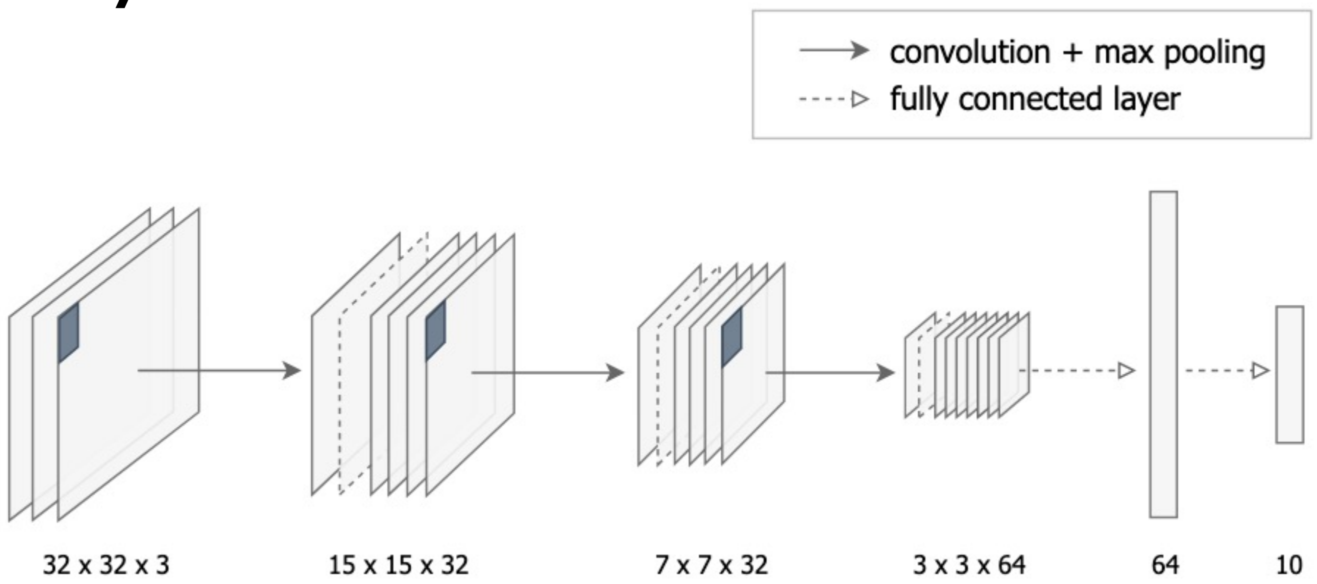
Transfer learning

exploiting already performed training on a large dataset

utilize knowledge acquired for one task and leverage it to solve another similar task

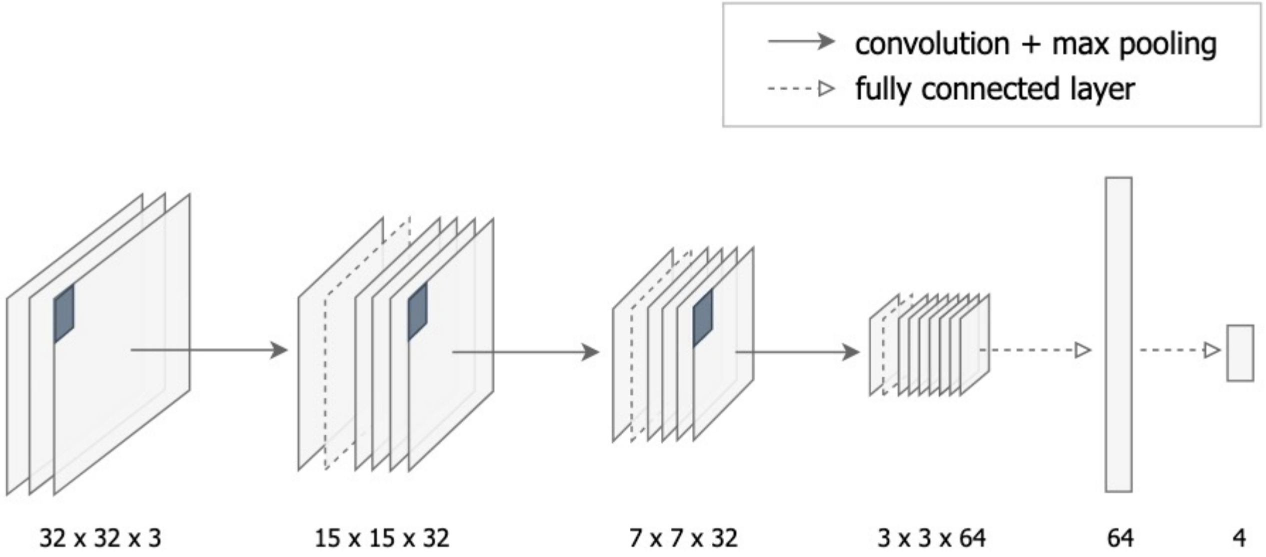
General image classifier

- CNN general image classifier taken as basis: **Cifar10Net**
  - **Input**: $32 \times 32 \times 3$ RGB images
  - **Output**: classification among 10 categories
- Benefits of tuning a pre-trained model?
  - Reduced requirements of training data and computing capacity
- **Architecture adaptation is necessary**
  - Output unit adaptation
  - Input unit adaptation



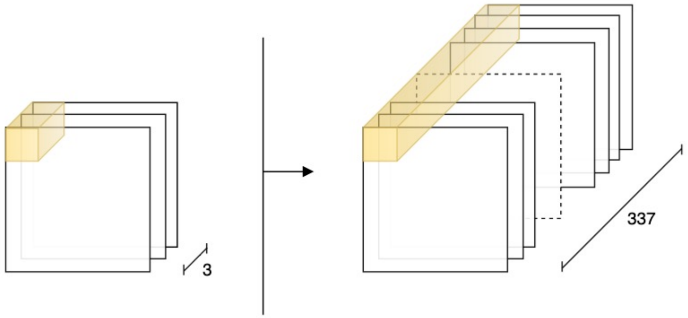
Output unit adaptation

- Modify last Fully Connected Layer to match **4** instead of 10 categories
- Weights and biases are analysed and re-used to initialize the new last FC layer
- After experiments, tuning the **last two FC** layers results to be the best option



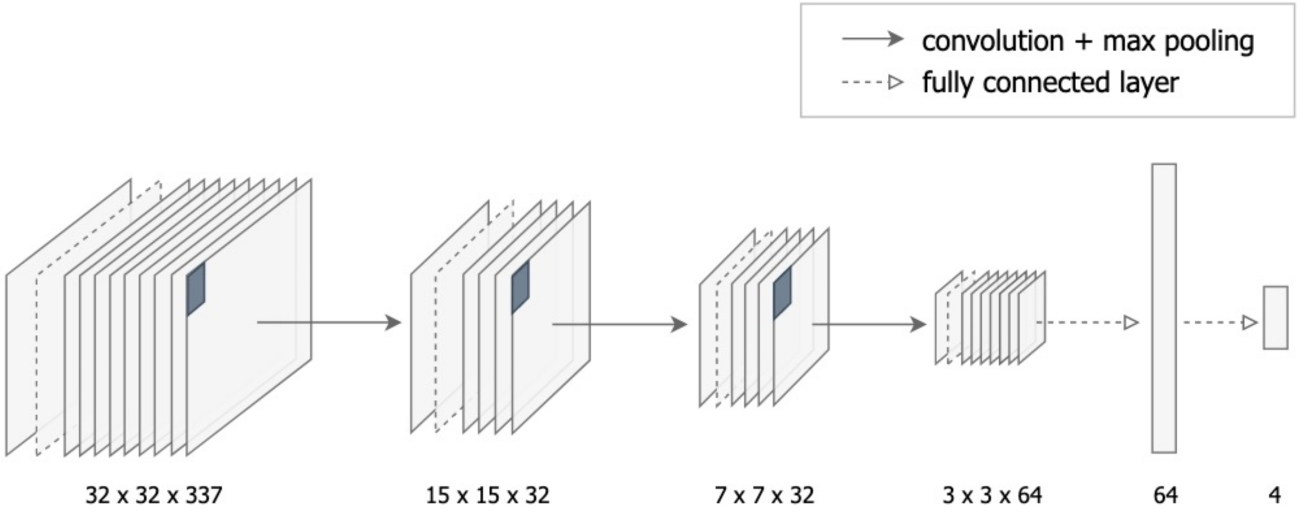
Input unit adaptation

- Modify first Convolution Layer to match **the multitude of spectral bands**



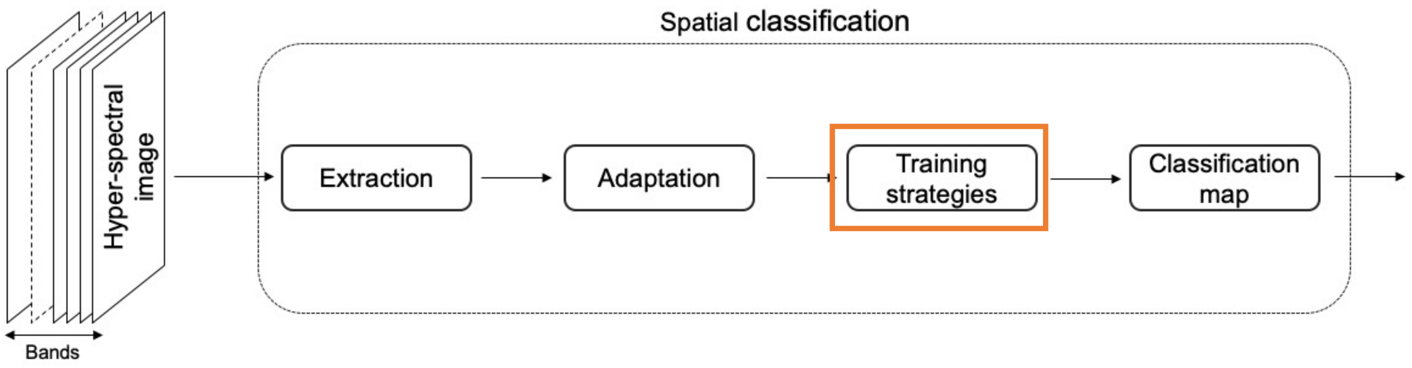
- Weights and biases are analysed and re-used to initialize the first Conv layer
- After experiments, tuning the **first Conv** layer results to be the best option

Final modified network architecture



Spatial classification

- Extraction
- Adaptation
- **Training strategies**
- Classification map



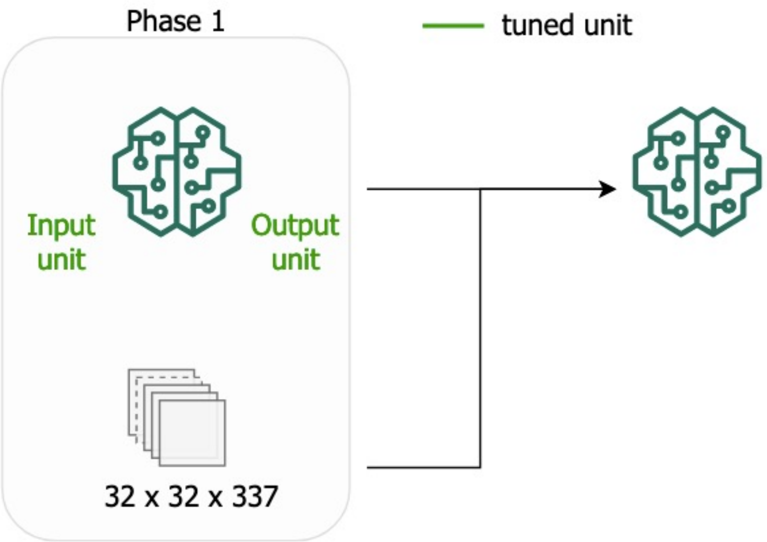
Training phase

- Modified architecture is able to handle the extracted HS sub-cuboids
- Three different training strategies are applied
- The entire network is never trained: input and output units are tuned, with the in-between layers kept frozen

- Training parameters:
  - Epochs: 1500
  - Minibatch size: 50
  - Stochastic gradient with momentum (SGDM)
  - Momentum: 0.9

Training strategies

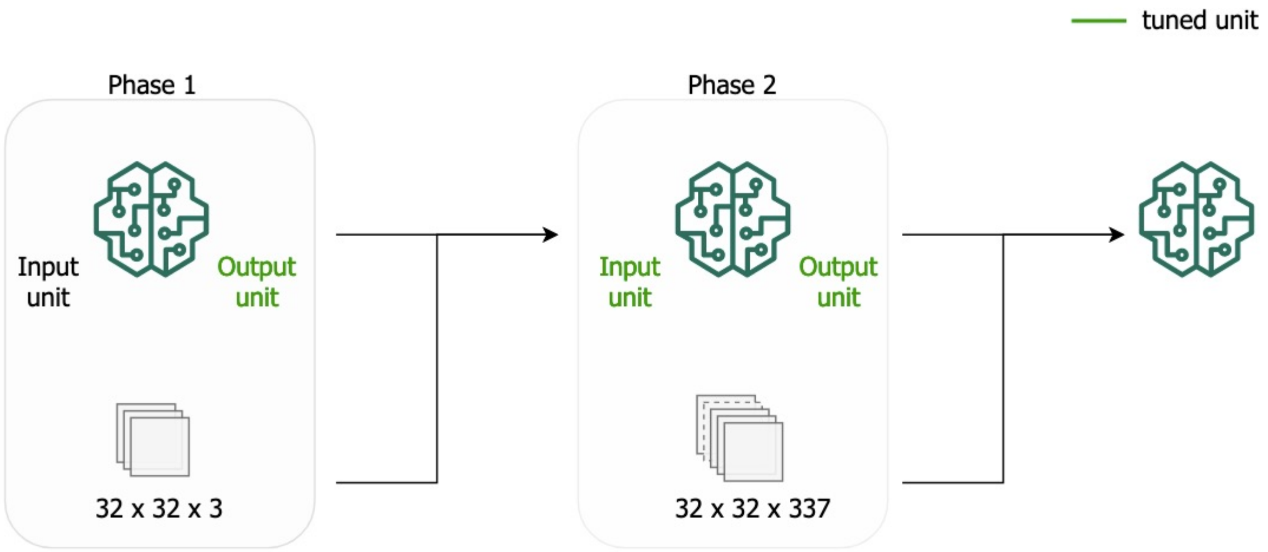
- **Strategy I**
- Strategy II
- Strategy III



- One-phase training process, where both input and output units are trained

Training strategies

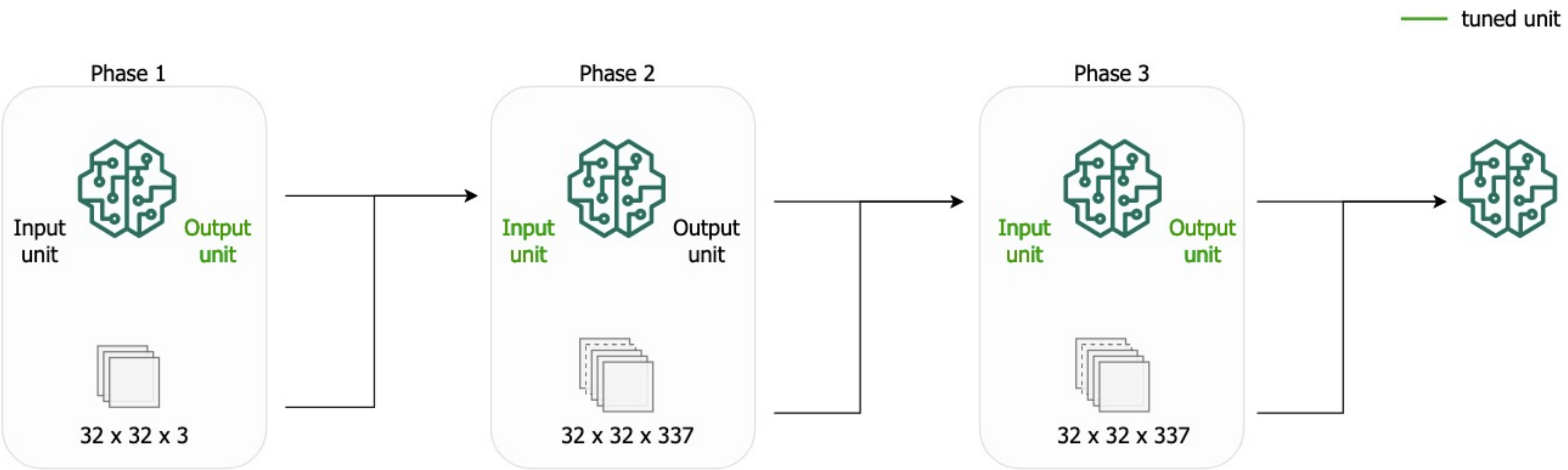
- Strategy I
- **Strategy II**
- Strategy III



- Two-phases training process, where
  - output unit is trained in Phase 1
  - both input and output units are trained in Phase 2

Training strategies

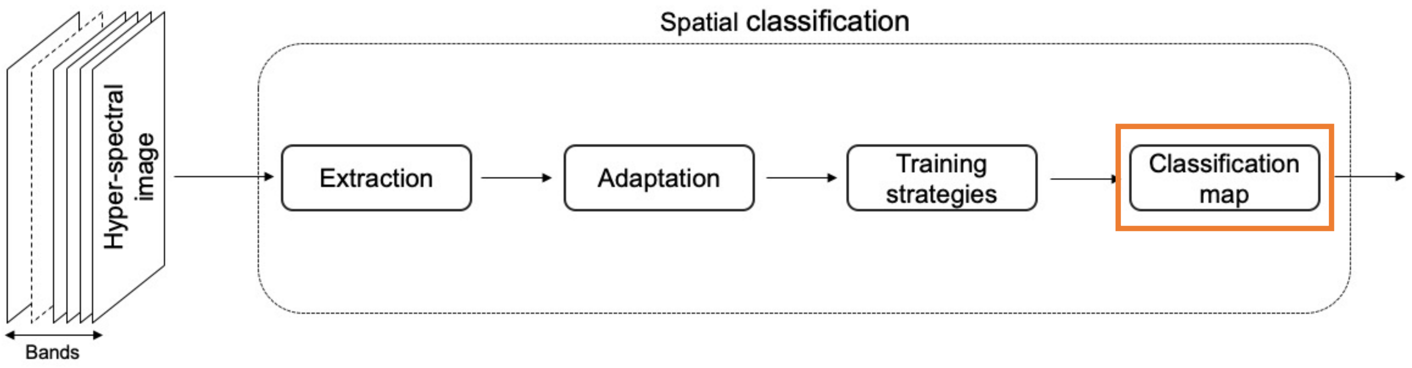
- Strategy I
- Strategy II
- **Strategy III**



- Three-phases training process, where
  - output unit is trained in Phase 1
  - input unit is trained in Phase 2
  - both input and output units are trained in Phase 2

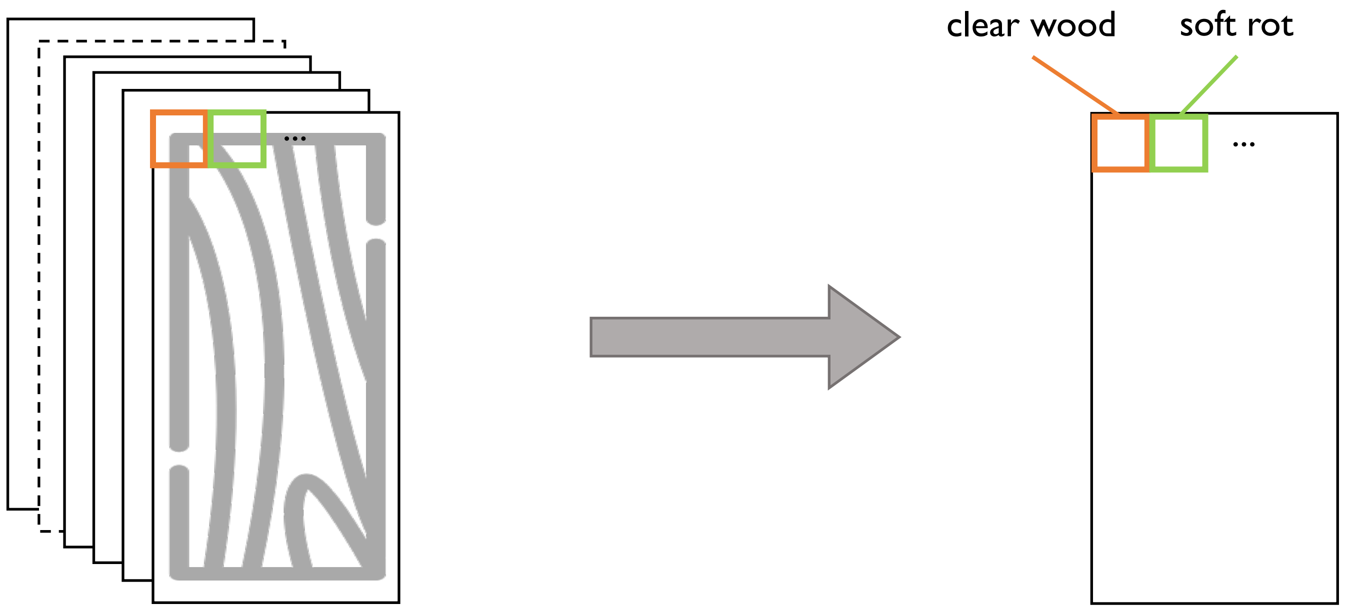
Spatial classification

- Extraction
- Adaptation
- Training strategies
- **Classification map**



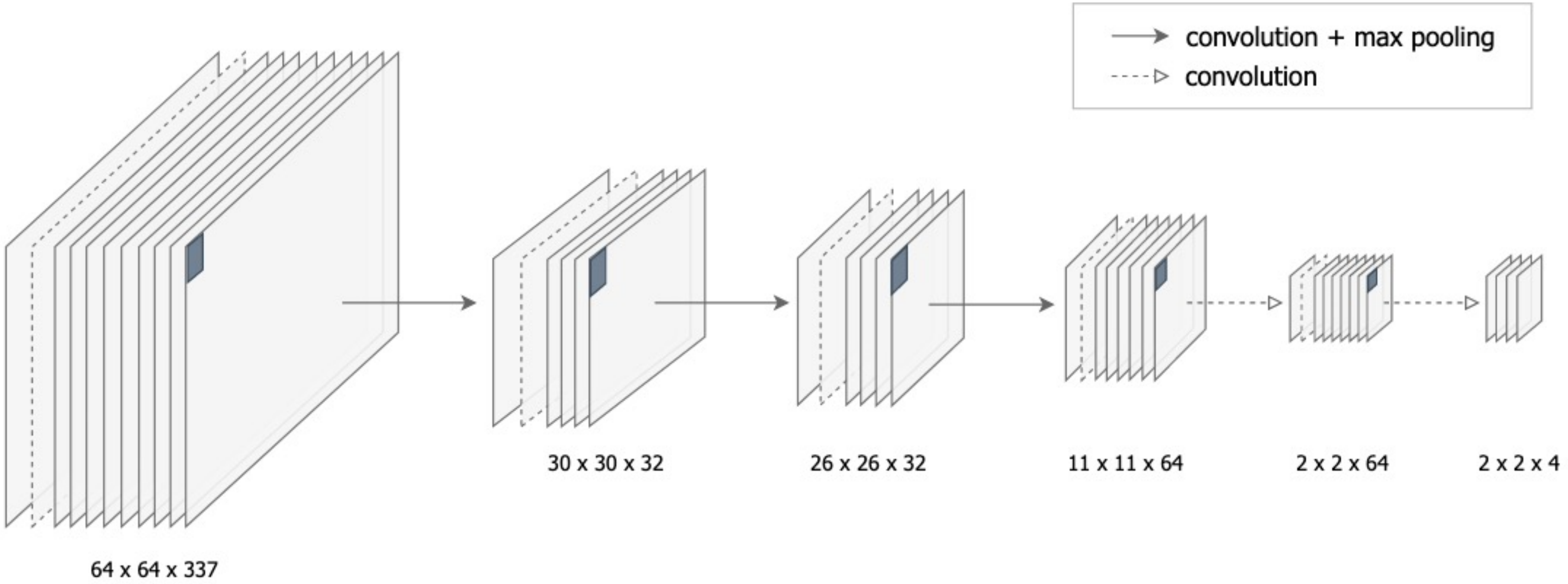
Classification map

- Developed CNN-based HS classifier takes as input $32 \times 32 \times 337$ images
- Final goal is to produce a **classification map of arbitrary size HS images**



Fully Convolutional Network

- CNN architecture is not enough: FC layers constraint the input dimension
- Conversion into **Fully Convolutional Network**
  - Dense part → Convolutional part
  - FC layers → Conv layers
- Produce a classification map for each 32×32 spatial region of input image



Outline

Problem statement

Problem solution

Results

Training strategies evaluation

- Experiments performed with different configurations of learning rates
- Results are validated by running each independent experiment 5 times
- Evaluation in term of testing accuracy

Average accuracy
(all learning rate configurations)

Highest accuracy
(best learning rate configuration)

Training strategies evaluation

- Experiments performed with different configurations of learning rates
- Results are validated by running each independent experiment 5 times
- Evaluation in term of testing accuracy

	Strategy I
Average accuracy (all learning rate configurations)	~80%
Highest accuracy (best learning rate configuration)	~83%

Training strategies evaluation

- Experiments performed with different configurations of learning rates
- Results are validated by running each independent experiment 5 times
- Evaluation in term of testing accuracy

	Strategy I	**Strategy II**
Average accuracy (all learning rate configurations)	~80%	~81%
Highest accuracy (best learning rate configuration)	~83%	~87%

Training strategies evaluation

- Experiments performed with different configurations of learning rates
- Results are validated by running each independent experiment 5 times
- Evaluation in term of testing accuracy

	Strategy I	**Strategy II**	**Strategy III**
Average accuracy (all learning rate configurations)	~80%	~81%	**~82%**
Highest accuracy (best learning rate configuration)	~83%	~87%	**~89%**

Considerations

- Strategy III is the best training strategy, in term of accuracy and stability
- An improvement in both average and highest accuracy is registered from one strategy to another

↓

The inclusion of in-between tuning phases brings benefit to the classifier performance

Considerations

Research question #1

Is it possible to develop an hyperspectral spatial classifier on the basis of a pre-trained general image classifier?

Yes. By adapting input and output unit and training it following strategy III, we developed an HS spatial classifier that reaches ~89% of accuracy

Clear wood VS wood affected by fungi

Scenario in which it is important to classify healthy wood from wood affected by fungi

The classifier is trained by classifying only elements of this two classes

Fungi classes are combined together

From multi-class to binary classification

Clear wood VS wood affected by fungi

Scenario in which it is important to classify healthy wood from wood affected by fungi

The classifier is trained by classifying only elements of this two classes

Fungi classes are combined together

From multi-class to binary classification

Predicted values

True		clear wood	fungi
	clear wood	90	1
	fungi	4	87

	Precision	Recall
clear wood	0.968	0.989
fungi	0.989	0.978

Accuracy: ~98%

Research question #2

Is the HS spatial classifier able to distinguish between clear wood and wood affected by fungi?

Yes. The developed classifier distinguishes between the two categories with an accuracy of around 98%

Soft rot VS brown stain

- From the results, instances of *soft rot* and *brown stain* are confused with each other
- The classifier is trained by classifying only elements of this two classes

Predicted values

True		soft rot	brown stain
	soft rot	28	8
	brown stain	7	28

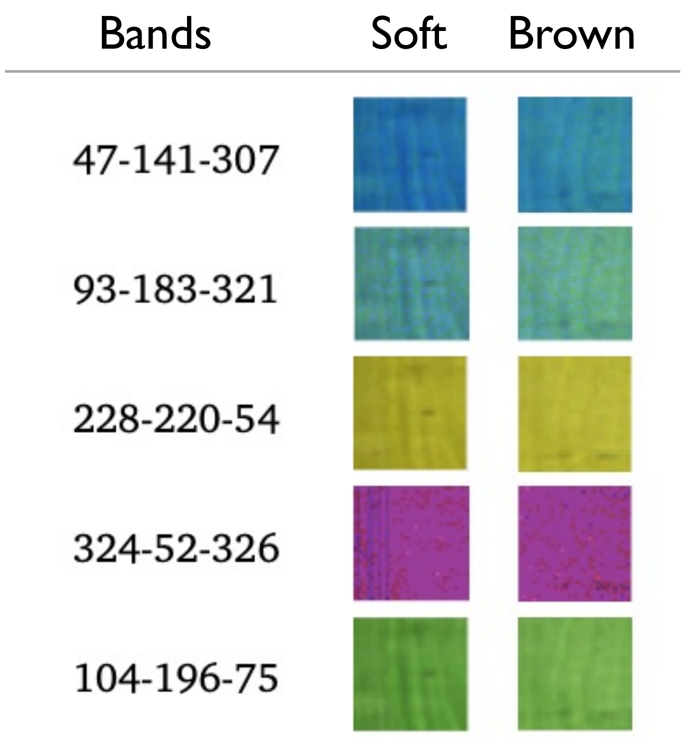
	Precision	**Recall**
soft rot	0.800	0.778
brown stain	0.778	0.800

Accuracy: ~80%

Soft rot VS brown stain

- Deeper analysis shows that the two classes share spatial and spectral information

- Misclassification may lie in their nature
  - Soft rot is the natural evolution of brown stain
  - Distinction is **tactile**, differences in consistency rather than visual appearance



Soft rot VS brown stain

Research question #3

Is the HS spatial classifier able to recognize the different categories of wood fungi?

Not optimally. The developed classifier distinguishes with 80% the *soft rot* and *brown stain* classes, due to their spatial and spectral similarity

Brown

Classification map

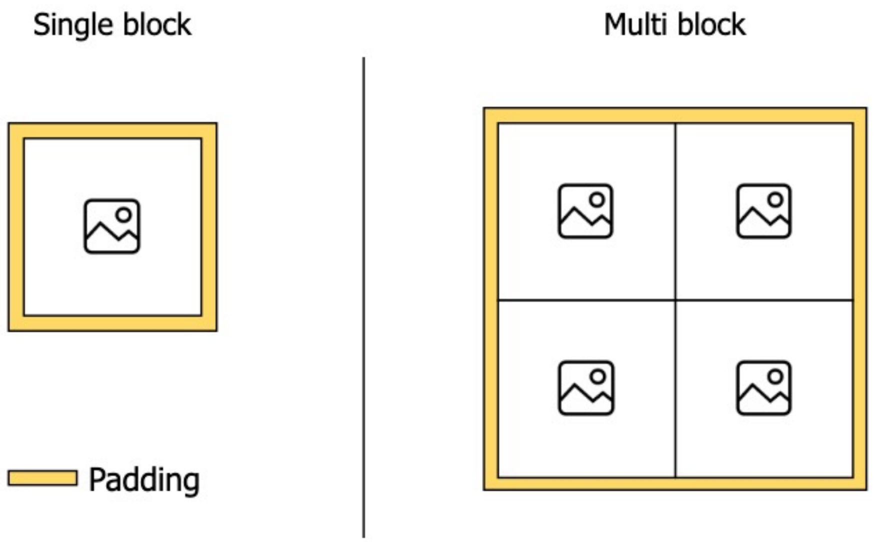
- After the multi-block conversion, the accuracy resulted to drop once it is tested on multi-block data

Classifier	Testing data	Accuracy
single-block	single-block	88.89%
multi-block	single-block	88.89%
multi-block	multi-block	75.00%

- Possible explanation: the presence of padding in the network architecture

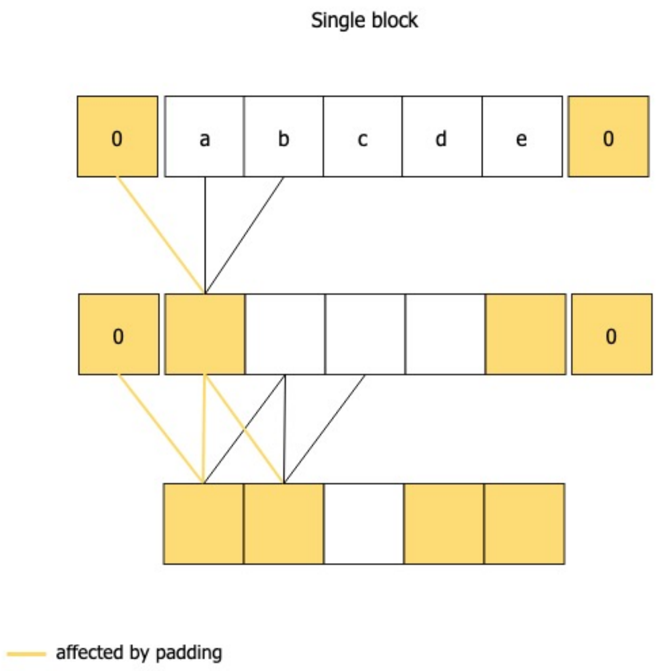
Classification map: effect of padding

- **Single-block classifier**: trained with padding, the entire spatial image is surrounded by 0s
- **Multi-block classifier**: padding is added around the entire image, internal padding is absent



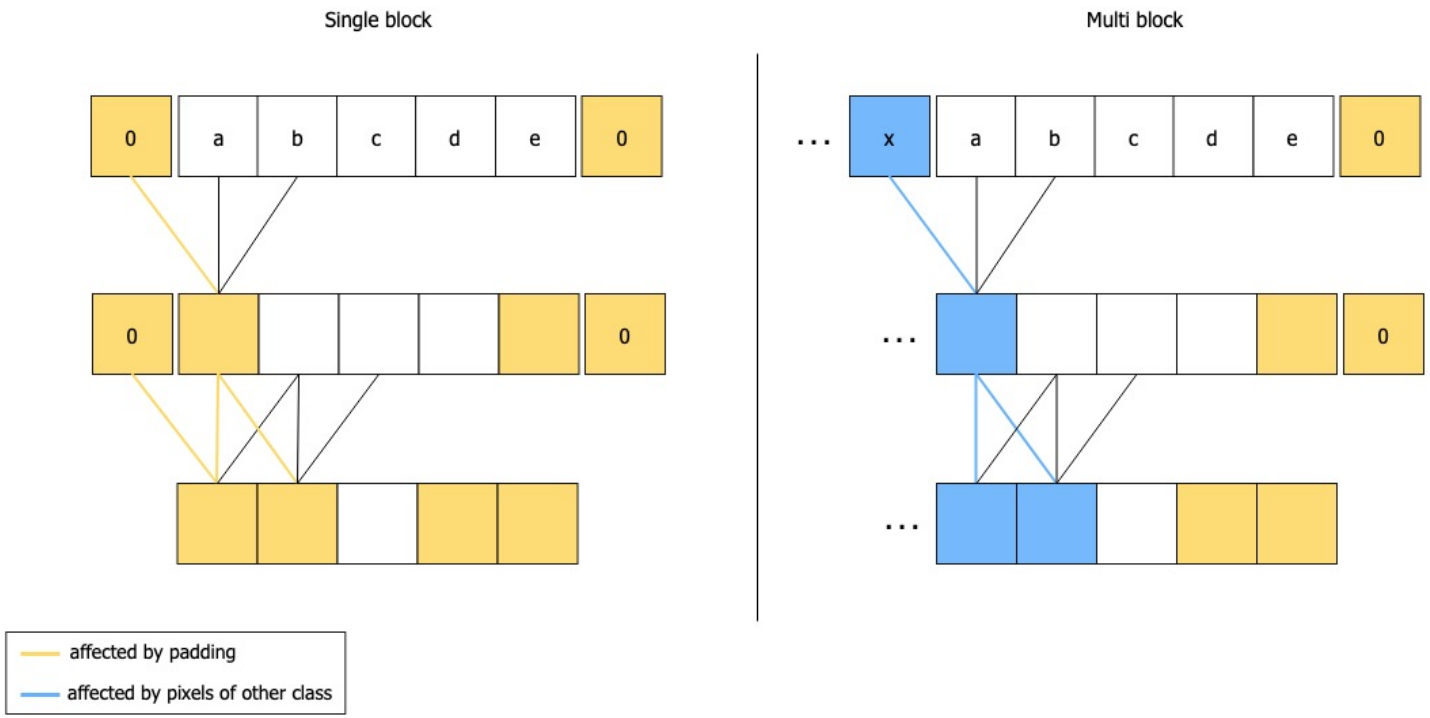
Classification map: effect of padding

- **Single-block classifier**
  - some neurons are affected by padding
  - as we go deeper in the network, the more neurons are affected by padding



Classification map: effect of padding

- **Multi-block classifier**
  - some neurons are affected by features belonging to other categories
  - as we go deeper in the network, the more neurons are affected
  - neurons in the final layers are influenced by a mixture of pixels of different categories



Classification map

- Padding is therefore removed from the architecture. Two approaches:

Classification map

- Padding is therefore removed from the architecture. Two approaches:
  - Removed after training

Padding removed after training

Classifier	Testing data	Accuracy
single-block	single-block	60.16%
multi-block	single-block	60.16%
multi-block	multi-block	60.16%

Classification map

- Padding is therefore removed from the architecture. Two approaches:
  - Removed after training
  - Removed before training

Padding removed after training

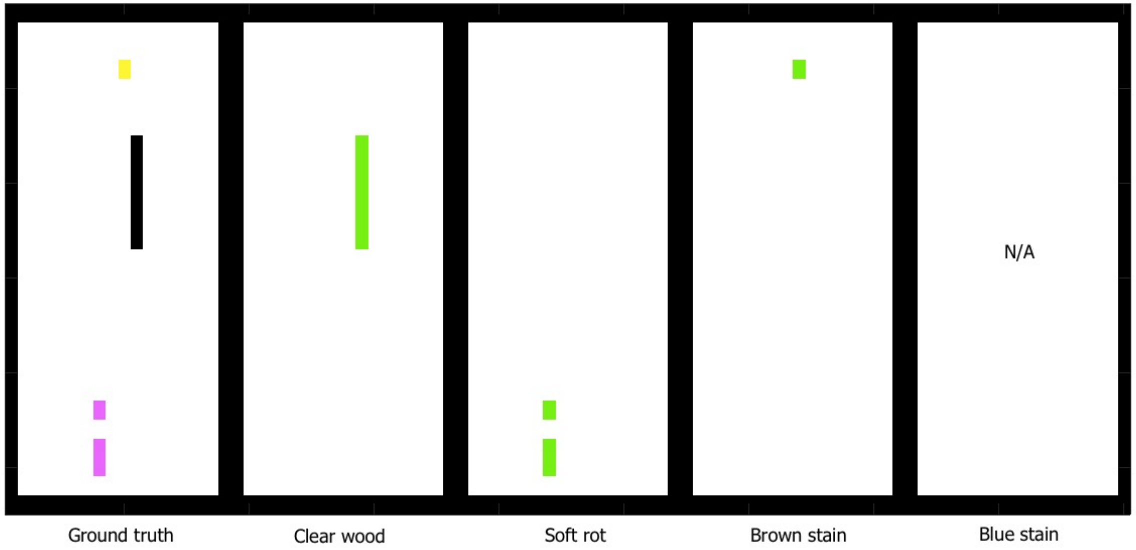
Classifier	Testing data	Accuracy
single-block	single-block	60.16%
multi-block	single-block	60.16%
multi-block	multi-block	60.16%

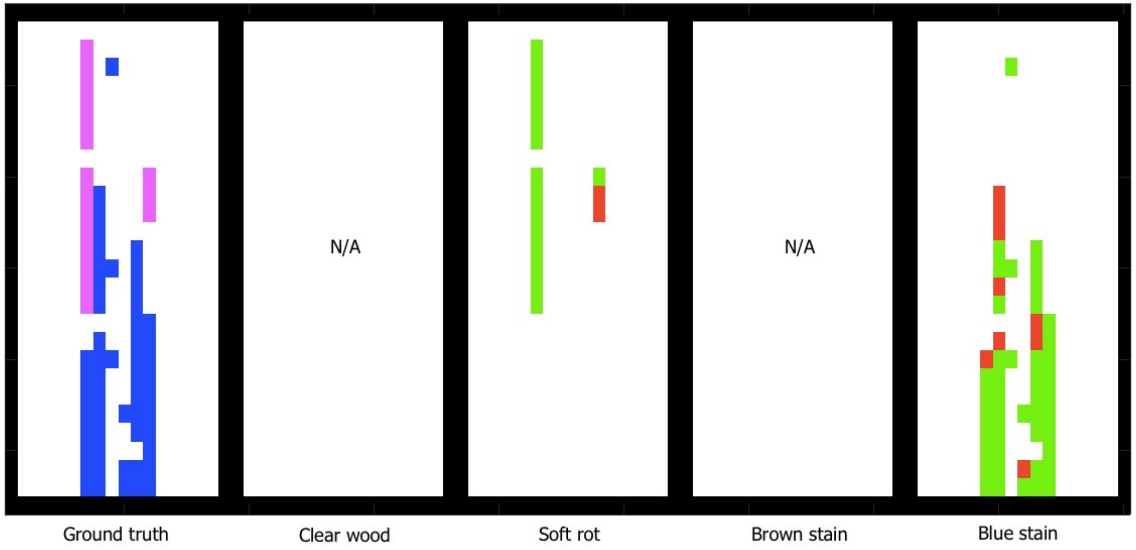
Padding removed before training

Classifier	Testing data	Accuracy
single-block	single-block	90.63%
multi-block	single-block	90.63%
multi-block	multi-block	90.63%

Classification map: examples

— clear wood
— brown stain
— correctly classified
— soft rot
— blue stain
— wrongly classified

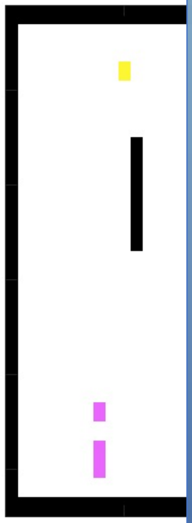




Classification map: examples

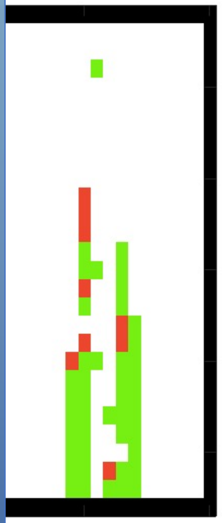
Research question #5

Is it possible to convert an hyperspectral single-block classifier into a multi-block classifier to produce a classification map of any wooden board?



Ground truth

Yes. After removing padding, training the classifier and converting it to a Fully Convolutional Network, the multi-block classifier produced a classification map with an accuracy of ~91%



Blue stain

Training time

Simulations were carried out on two different machines

CPU-based

GPU-based

Reported results, for strategy III

CPU: 323 min

GPU: 132 min

As a result, the developed classifier can be trained in reasonable time on a commonly available CPU-based computer

Future works

Investigate techniques to improve *soft rot* and *brown stain* distinction (discover differences at molecular level)

Extend experiments on new and larger available dataset (300Gb)

Completion of conceptual framework

- Development of spectral classifier
- Resampling and fusion techniques to combine the classifiers' results

Thanks!

https://h2i.inf.unibz.it/

h2i-fesr@googlegroups.com