Biomedical Image Classification with Random Subwindows and Decision Trees

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Abstract

In this paper, we address a problem of biomedical image classification that involves the automatic classification of x-ray images in 57 predefined classes with large intra-class variability. To achieve that goal, we apply and slightly adapt a recent generic method for image classification based on ensemble of decision trees and random subwindows [MGPW05]. We obtain classification results close to the state of the art on a publicly available database of 10000 x-ray images. We also provide some clues to interpret the classification of each image in terms of subwindow relevance.

Image Classification

▷ Goal:

Given a set of training images labelled into a finite number of classes, the goal of an automatic image classification method is to build a model that will be able to predict accurately the class of new, unseen images.

▷ Biomedical applications:

Organize large-scale image databases into categories without limitation to a specific diagnostic study, setup clinical diagnosis tools, provide high-throughput cell phenotype screening, ...

▷ Some solutions:

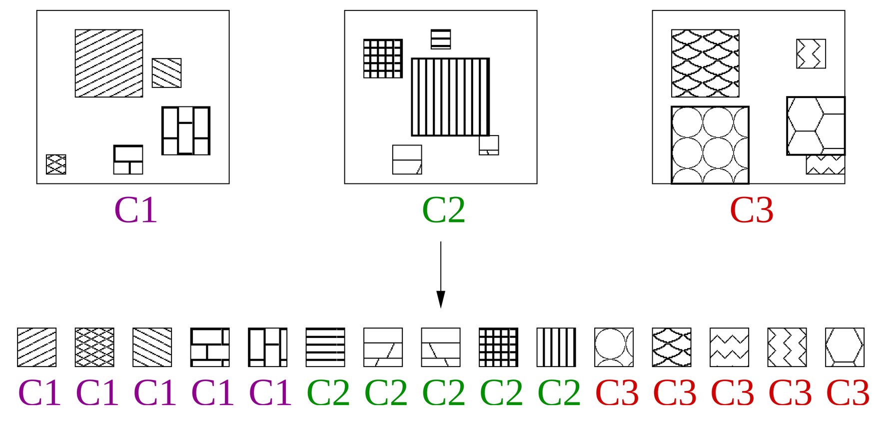
- Pre-processing "feature extraction" step, specific to the particular problem and application domain
- Features used as new input variables for traditional learning algorithms (nearest neighbor or neural network classifiers)

Random Subwindows and Decision Trees

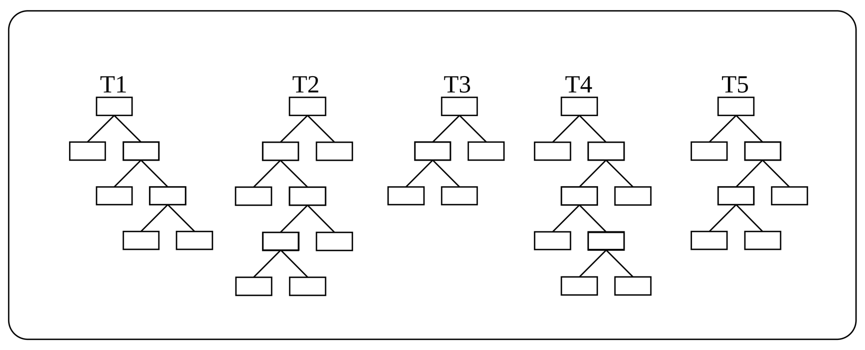
▷ Concepts

- Extraction of a large number of possibly overlapping, square subwindows of random sizes and at random positions
- Pixel-based description with scale normalization
- Tree-based machine learning ensemble methods
- Successfully applied to household objects, buildings, landscape themes, handwritten digits, faces, ...

▷ Learning stage



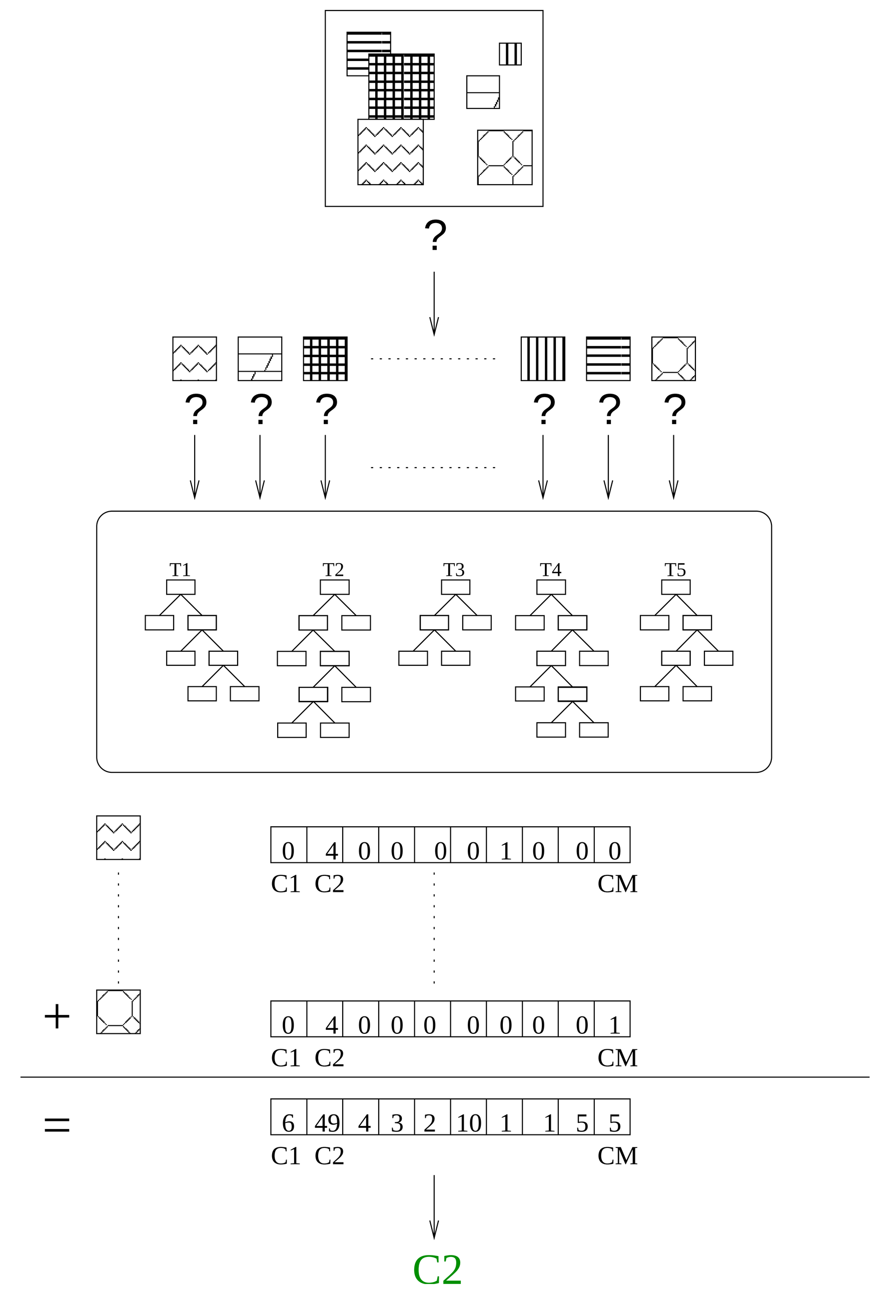
- Class-balanced extraction of (N_w) subwindows: from each training image of class c, we extract $N_w/(m * nb_c)$ subwindows where m is the number of classes and nb_c the number of training images of class c
- Subwindow resizing down to a fixed size (16×16 pixels)
- Subwindow labeling as its parent image class



- Building a subwindow classification model using supervised methods
- Ensemble of T decision tree methods: Tree Boosting, Extra-Trees [GEW06]

Random Subwindows and Decision Trees (continued)

▷ Prediction stage



- Extraction of $N_{w,test}$ subwindows in test image
- Propagation of each subwindow into each tree
- Aggregation of tree votes. We assign to the image the majority class among the classes assigned to its subwindows.

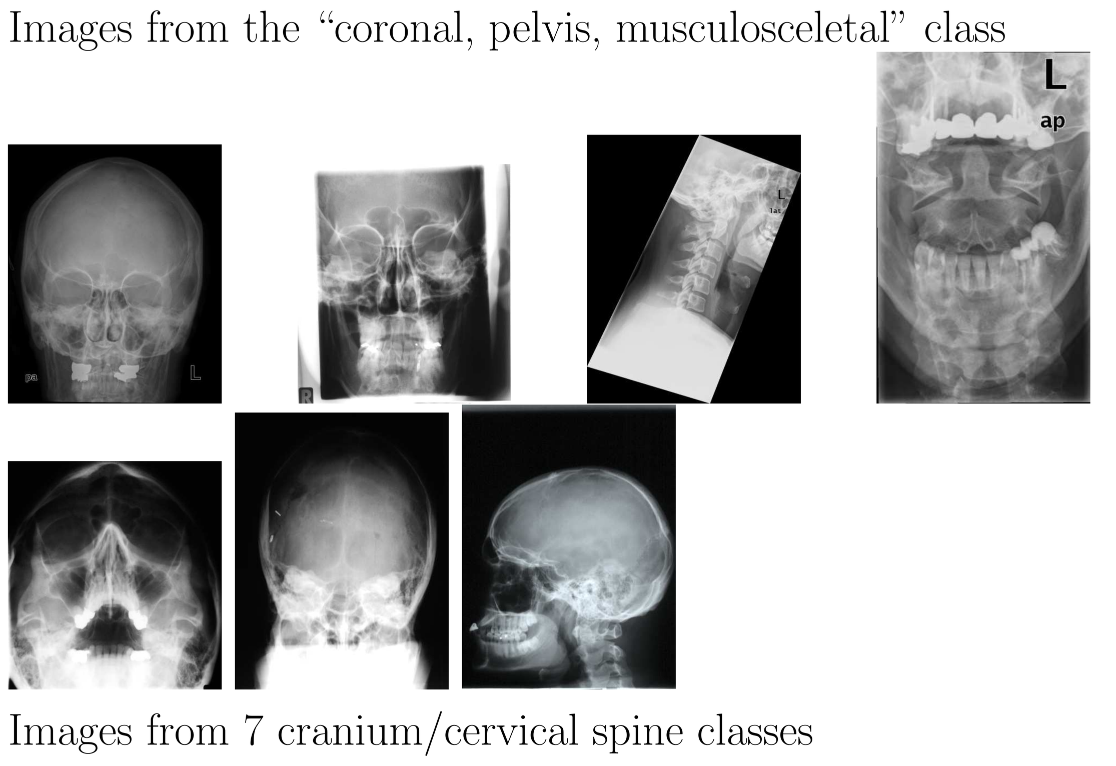
Dataset: IRMA challenge

▷ Description

- 10000 x-ray images (courtesy of TM Lehmann, RWTH, Aachen, Germany, http://www.irma-project.org)
- 57 classes according to the IRMA code: different modalities, orientations, body parts, and biological systems

▷ Examples

Images from the "coronal, pelvis, musculosceletal" class



Images from 7 cranium/cervical spine classes

Protocol and Results

▷ Protocol and parameters

- Training set: 9000 images, test set: 1000 images ([iCS05])
- $N_w = 800000$, $T = 25$, $N_{w,test} = 500$

▷ Misclassification error rate

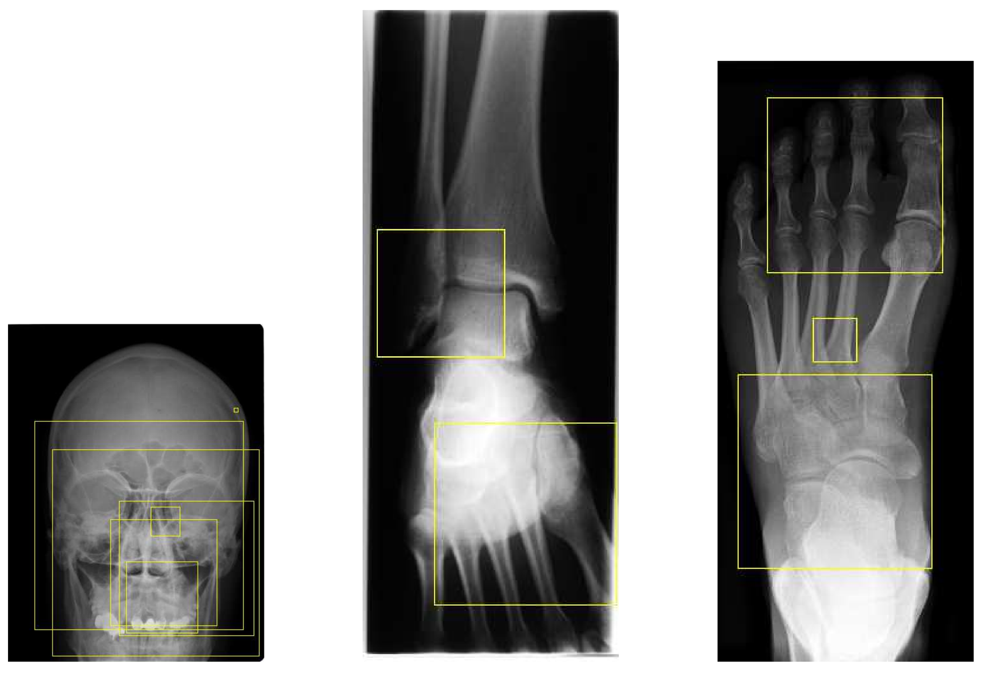
Method	*error rate*
1-NN + IDM [KGN04]	12.6%
1-NN + CCF + IDM + Tamura	13.3%
Discriminative patches [DKN05]	13.9%
Random Subwindows + Tree Boosting	14.0 %
MI1 Confidence	14.6%
Random Subwindows + Extra-Trees	14.7%
Gift 5NN8g	20.6%
...	...
Nearest Neighbor, 32×32, Euclidian	36.8%
...	...
Texture directionality	73.3%

▷ Computational Efficiency

- Training algorithm is on the order of $TN_w \log N_w$
- Prediction essentially proportional to $TN_{w,test} \log N_w$

Interpretability

- Well classified subwindows could bring potentially useful information about that class



Conclusion

- We applied our generic method [MGPW05] on a specific biomedical task
- We obtained results competitive with state-of-the-art algorithms without tedious adaptation. It confirms the potential of the approach for a wide range of applications.
- The possibility to extract interpretable information from images has been highlighted

References

[DKN05] T. Deselaers, D. Keysers, and H. Ney. Discriminative training for object recognition using image patches. In *Proc. International Conference on Computer Vision and Pattern Recognition (CVPR)*, volume 2, pages 157–162, June 2005.

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[KGN04] D. Keysers, C. Gollan, and H. Ney. Classification of medical images using non-linear distortion models. In *Bildverarbeitung für die Medizin (BVM)*, pages 366–370, March 2004.

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