M2CAI Workflow Challenge: Convolutional Neural Networks with Time Smoothing and Hidden Markov Model for Video Frames Classification

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Context

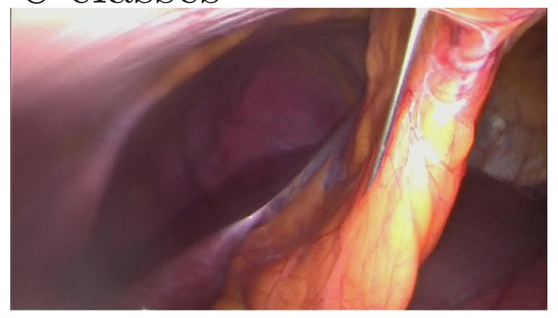
Goal: Surgical video frames classification

▷ Videos of size 1920x1080 Shot at 25 frames per second at IRCAD research center in Strasbourg, France

▷ 27 training videos

▷ 15 testing videos

▷ 8 classes



OK for centered object *KO for "natural" image*

▷ Online prediction: $P(y|x_i, x_{i-1}, x_{i-2}, \ldots)$

▷ Usefull to

▷ Monitor surgeons

▷ Trigger automatic actions

Our approach (usable in production)

▷ Firstly, we train a classifier using Deep Learning

▷ Secondly, we smooth its predictions

▷ Averaging predictions over last 15 frames

▷ Then, we use a Hidden Markov Model (HMM) as a "denoizer"

Frames classifier

Creating validation set by random split:

▷ Training set: 22 videos ▷ Validation set: 5 videos $\{2, 9, 10, 13, 27\}$

Extracting one frame every 25 frames (1 f/s):

▷ Training set: 59,493 images

▷ Validation set: 8,062 images

▷ Testing set: 28,732 images

3 approaches using Deep Learning:

▷ Training CNN From Scratch

▷ Good: learning representations for this task

▷ Bad: maybe not enough data + lot of hyperparameters

▷ Pre-trained CNN as Features Extractor + SVM

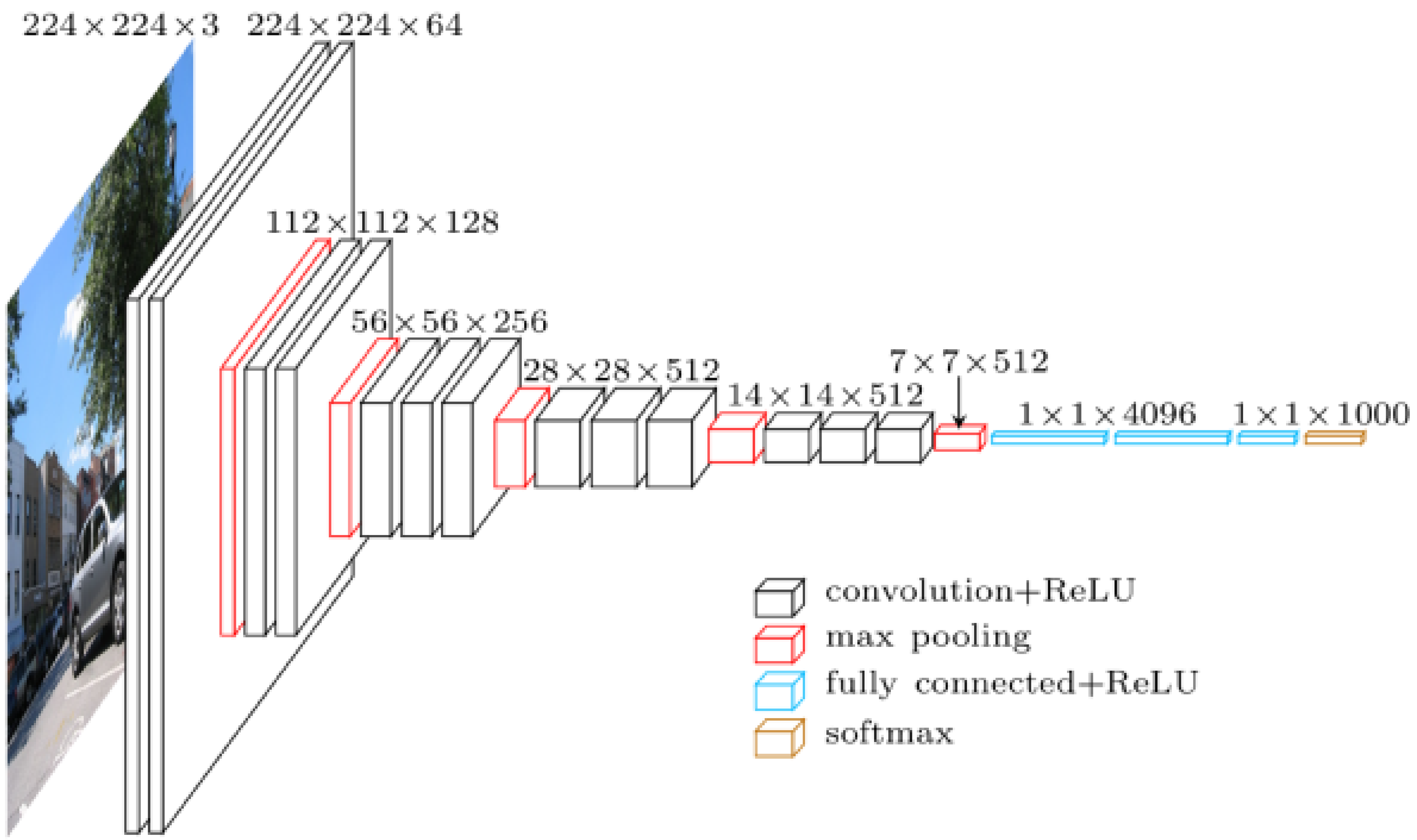
▷ Good: using (good) representations learned on ImageNet

▷ Bad: large semantic gab between ImageNet and this task

▷ Fine Tuning a pre-trained CNN

▷ Good: adapting the representations learned on ImageNet for this task

Deep learning architecture and methods



▷ Fully connected layer → convolution layer

▷ Sliding window approach / shared features

▷ Spatial aggregation

▷ Object localization prediction

Experiments

Model	Type	Accuracy (%)
InceptionV3	Extraction (repres. of ImageNet)	60.53
InceptionV3	From Scratch (repres. of M2CAI)	69.13
InceptionV3	Fine-tuning (both representations)	79.06
ResNet200	**Fine-tuning (both representations)**	**79.24**

Temporal Method	Accuracy Val (%)	Jaccard Val	Jac
Avg Smoothing	85.97	74.67	
Avg + HMM Online	**88.90**	**81.60**	
Avg + HMM Offline	93.47	87.59	

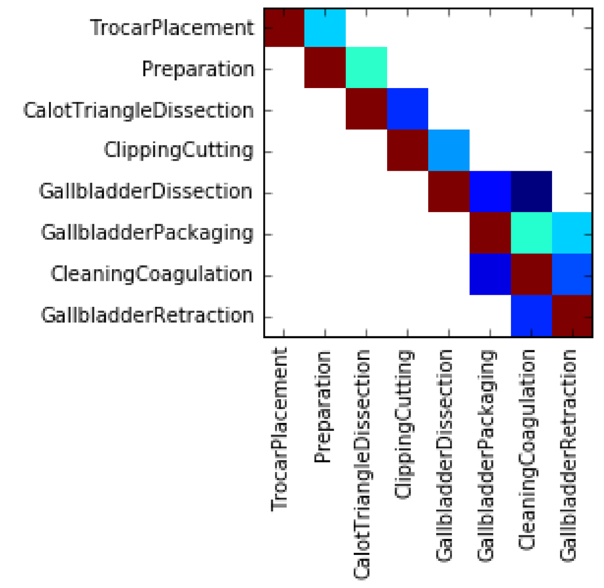
[1] Oquab et al. Is object localization for free? *CVPR*, 2015.
[2] Durand et al. MANTRA. *ICCV*, 2015.
[3] Parizi et al. Automatic discovery of parts. *ICLR*, 2015.
[4] Gong et al. Multi-scale orderless pooling. *ECCV*, 2014.

Hidden Markov Model

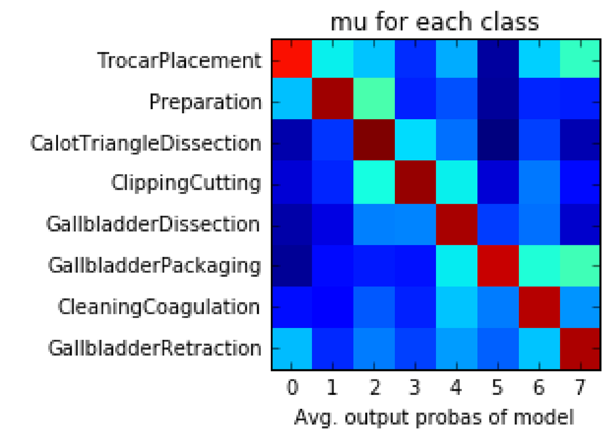
▷ Initial state probabilities

▷ Matrix of probabilities of transition between states

▷ Gaussian parameters for emissions of observations (mean and co-variance matrix)

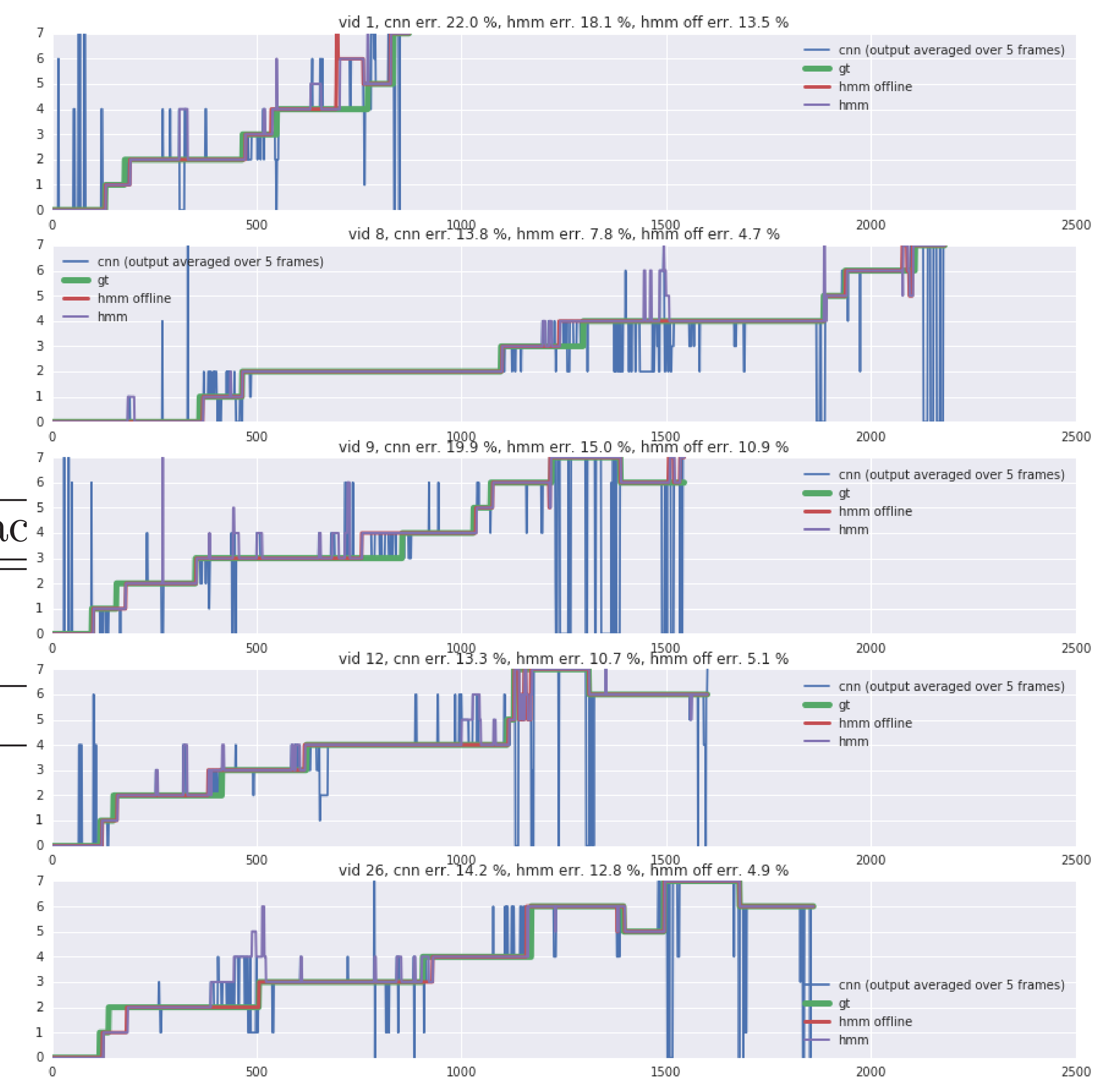


(b)



(c mean)

Visual results



Conclusion

▷ Fine Tuning most accurate approach ▷ HMM is usefull to smooth the predictions ▷ Production ready !

▷ Future Work: ▷ Fine Tuning CNN on full trainset ▷ Ensembling several fine tuned CNNs