

# Comparison of k-NN, SVM, and NN in Pit Pattern Classification of Zoom-Endoscopic Colon Images using Co-Occurrence Histograms

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# Project Team

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# Outline

Computer assisted diagnosis in colonoscopy may help to speed up the diagnosis process (by eventually replacing histological assessment) and may even improve the diagnosis accuracy.

In this work we employ and compare different classification techniques for an automated classification of visual data acquired by a magnifying colonoscope corresponding to a Pit Pattern classification scheme introduced recently.

Results are encouraging but are meant only to support human observation instead of replacing it. Interestingly, NN and SVM classifiers perform worse compared to a simple k-NN classification employing co-occurrence histograms as features.

# Introduction

According to the American cancer society colon cancer is the third most common type of cancer in males and fourth in females in western countries. Therefore a regular colon examination is recommended especially for people at an age of 50 years and older.

To obtain images which are as detailed as possible a special endoscope - a *magnifying endoscope* - can be used for colonoscopy. A magnification up to a factor of 150 is possible through an individually adjustable lens.

To visually enhance the structure of the mucosa and therefore the structure of an eventual tumorous lesion, a common procedure is to spray indigo carmine onto the mucosa which causes a plastic appearance of the mucosa.

## Pit Pattern Classification

Polyps of the colon are a frequent finding and are usually divided into metaplastic, adenomatous, and malignant. As resection of all polyps is time-consuming, it is imperative that those polyps which warrant endoscopic resection can be distinguished: polypectomy of metaplastic lesions is unnecessary and removal of invasive cancer may be hazardous. For these reasons, assessing the nature of lesions at the time of colonoscopy is important.

Correct diagnosis very much relies on the experience of the endoscopist as the interpretation of pit patterns may be challenging. Additionally, inter-observer variability of magnification chromoendoscopy has been described at least for Barrett's esophagus. Therefore, a supporting computer assisted classification scheme is highly desirable.

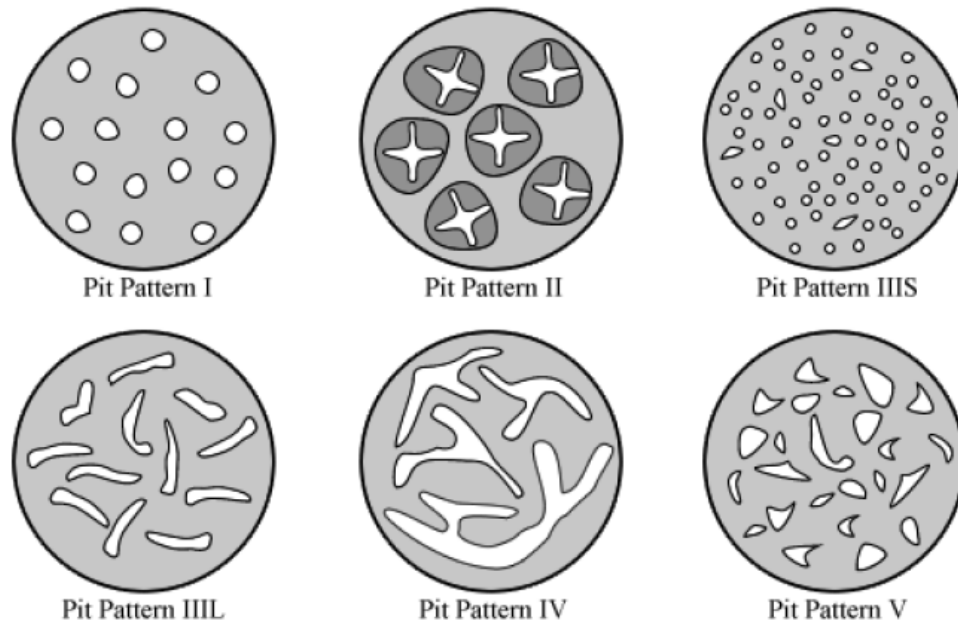
Diagnosis of tumorous lesions by endoscopy is always based on some sort of *staging*, which is a method used to evaluate the progress of cancer in a patient and to see to what extent a tumorous lesion has spread to other parts of the body. A recent classification system, based on so-called *pit patterns* of the colonic mucosa, was originally reported by Kudo et al.

## Pit Patterns: Definition

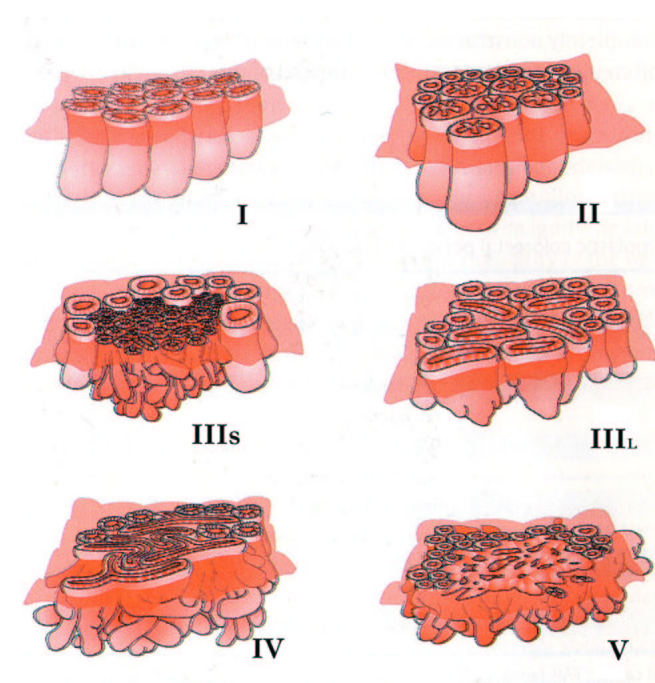
Pit Type	Characteristics
I	roundish pits which designate a normal mucosa
II	stellar or papillary pits
III S	small roundish or tubular pits, which are smaller than the pits of type I
III L	roundish or tubular pits, which are larger than the pits of type I
IV	branch-like or gyrus-like pits
V	non-structured pits

The higher the type number the higher is the risk of a lesion to be malignant: It has been suggested that type I and II pattern are characteristic of non-neoplastic lesions (which are benign), type III and IV are found on adenomatous polyps, and type V are strongly suggestive of invasive carcinoma. Types III - V can be grouped into neoplastic lesions which results in a coarser grouping of lesions into 2 instead of 6 classes.

# Pit Patterns: Visualization



2-D visualization

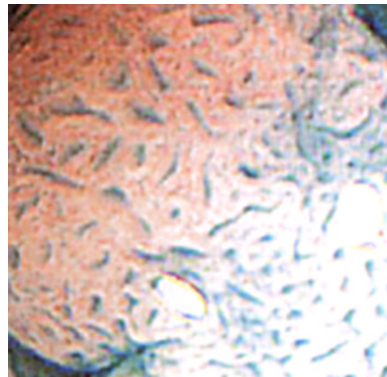


3-D visualization

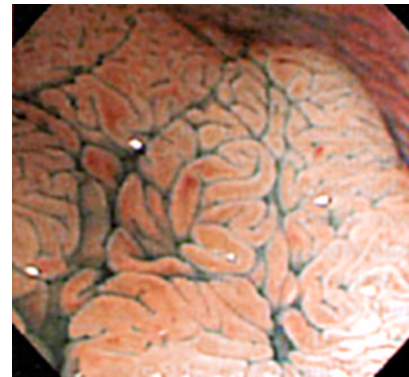
## Pit Patterns: Visual Examples



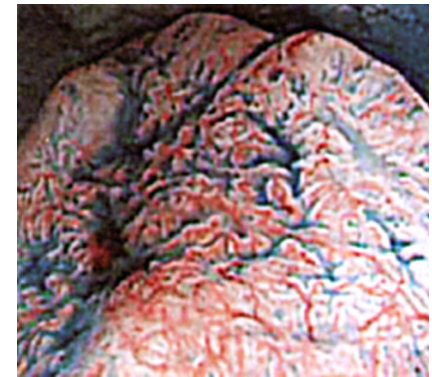
Type I



Type III



Type IV



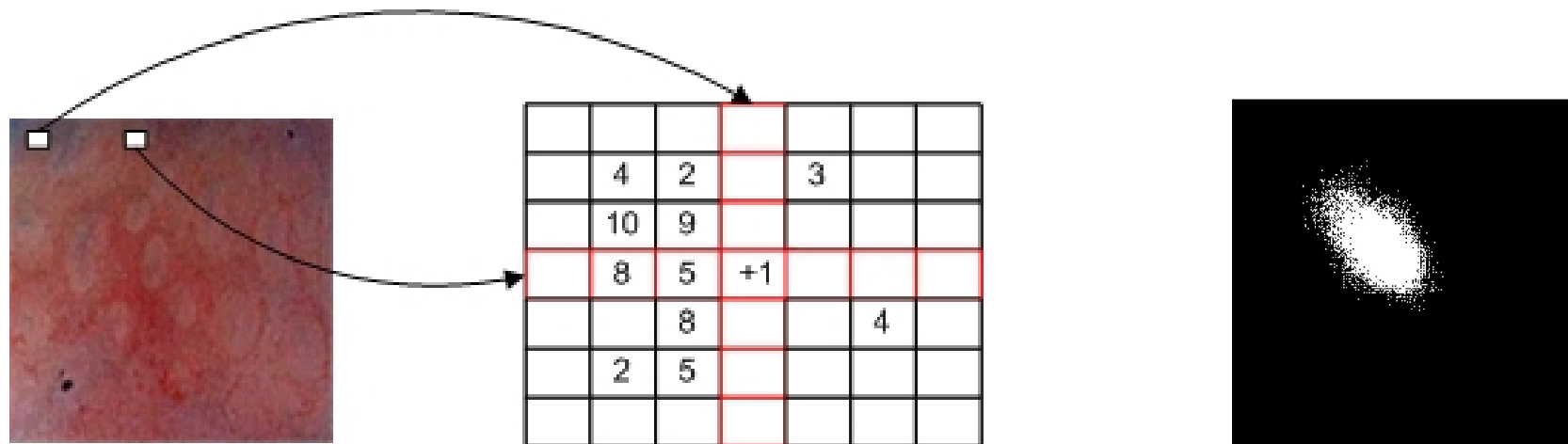
Type V

It is obvious that the clear abstract definition of pit patterns does not exactly carry over to real-world image material !



# Feature Extraction: Co-Occurrence Histograms

The co-occurrence histogram counts the number of pairs of pixels exhibiting specific color or luminance values that occur at certain separation distances in image space. Therefore, the CH adds geometric information to the classical color histogram, which abstracts away all geometry. By adjusting the distances over which we check co-occurrences, we can adjust the sensitivity of the algorithm. We use horizontal and vertical adjacency as separation distance and construct the CH out of the luminance channel Y. This results in a 2-dimensional histogram where the luminance values of the two adjacent pixels represent the two dimensions, each with 256 bins.



## Classification: k-NN

Classification of an input feature vector  $\vec{x}$  is done by determining the  $k$  closest training vectors according to a suitable distance metric. The vector  $\vec{x}$  is then assigned to that class to which the majority of those  $k$  nearest neighbours belong to. Given a pair of histograms,  $H(I)$  and  $H(I')$ , of images  $I$  and  $I'$ , respectively, each containing  $n$  bins, the histogram intersection of the normalized histograms is defined as follows:

$$H(I) \cap H(I') = \sum_{j=1}^n \min(H_j(I), H_j(I'))$$

For two images, the larger the value of the histogram intersection, the more similar the image pair is deemed to be.



## Classification: ANN

We use a 3-layer feed forward neural network with non-linear transfer functions (logarithmic-sigmoid) in the hidden and output layer. The resilient back propagation algorithm is employed. The number of input neurons has been set equal to size of the feature vector obtained from the the PCA feature selection and the number of output neurons is fixed to the number of classes.

To ensure that the back-propagation algorithm converges to the global minimum of error instead of a less optimal minimum the initial layer weights have to be optimized. Therefore a high number of randomly created configurations have been evaluated based on equal input data with regard to the average classification accuracy, to find a setting near the global minimum. The most promising initial layer weights have been stored in a file and used for all later investigations.

## Classification: SVM

Concerning SVM classification, the LIBSVM library is used. We conduct a naive grid search to find the best parameter choices for our classification purpose. The applied SVM classifier is a  $\nu$ -soft margin version with one-against-one approach and a RBF-Kernel. For optimal classification performance both the Kernel parameter  $\gamma$  and the soft margin parameter  $0 < \nu < 1$  have been optimized with regard to the average classification accuracy. The best results have been achieved for  $\gamma = 0.1$  and  $\nu = 0.5$ . To enable classification the input data have been normalized to values between  $[+1,-1]$ .

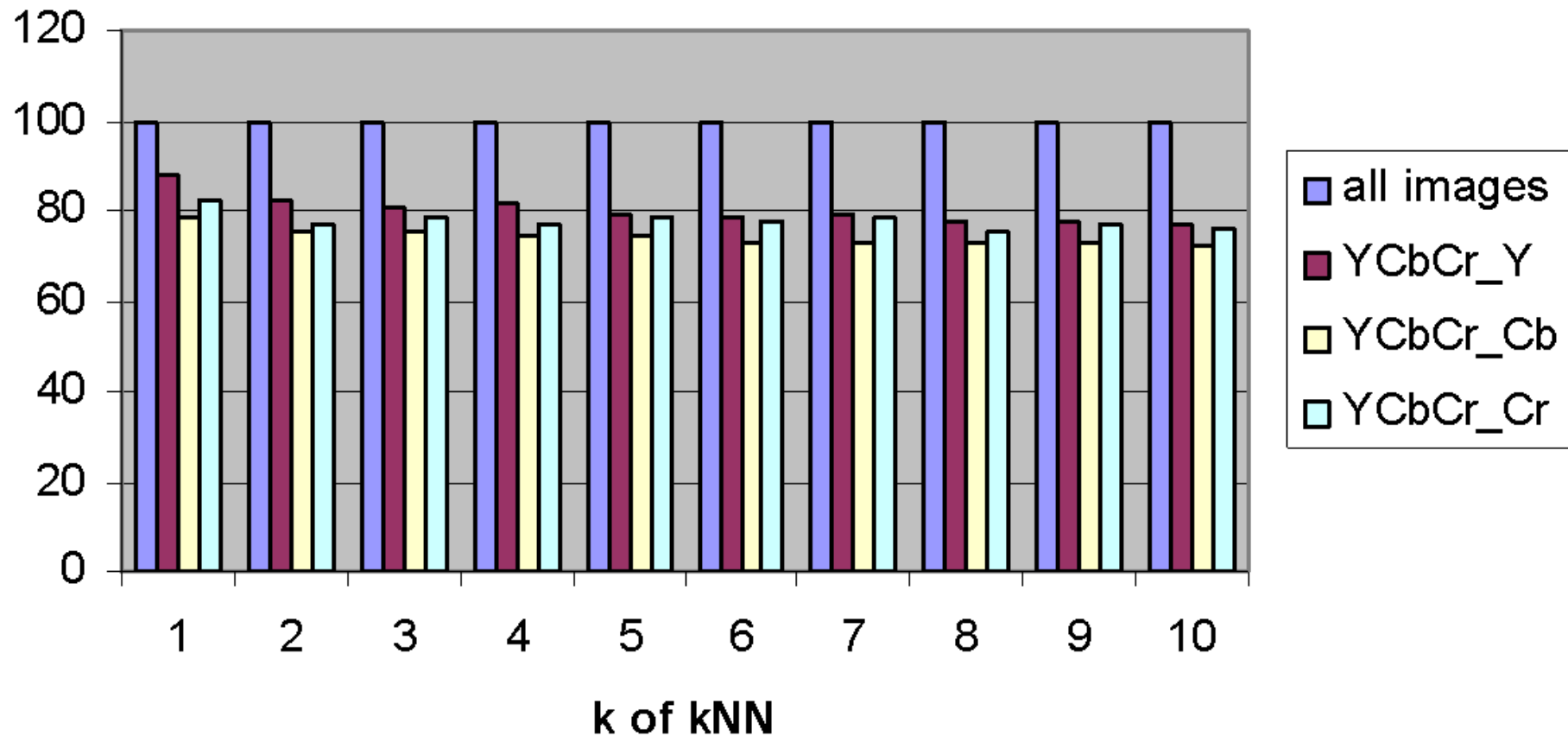
## Experimental Study

In our experiments we use 484 images acquired in 2005/2006 at the Department of Gastroenterology and Hepatology (Medical University of Vienna) using a zoom-colonoscope (Olympus Evis Exera CF-Q160ZI/L) with a magnification factor set to 150. Lesions found during colonoscopy have been examined after application of dye-spraying with indigocarmine. Biopsies or mucosal resection have been performed in order to get a histopathological diagnosis. Biopsies have been taken from type I, II, and type V lesions, as those lesions need not to be removed or cannot be removed endoscopically. Type III and IV lesions have been removed endoscopically. Out of all acquired images, histopathological classification resulted in 198 non-neoplastic and 286 neoplastic cases.

Pit Type	2 cls.	I		II			
	6 cls.	I	II	IIIS	IIIL	IV	V
Images		126	72	18	62	146	60

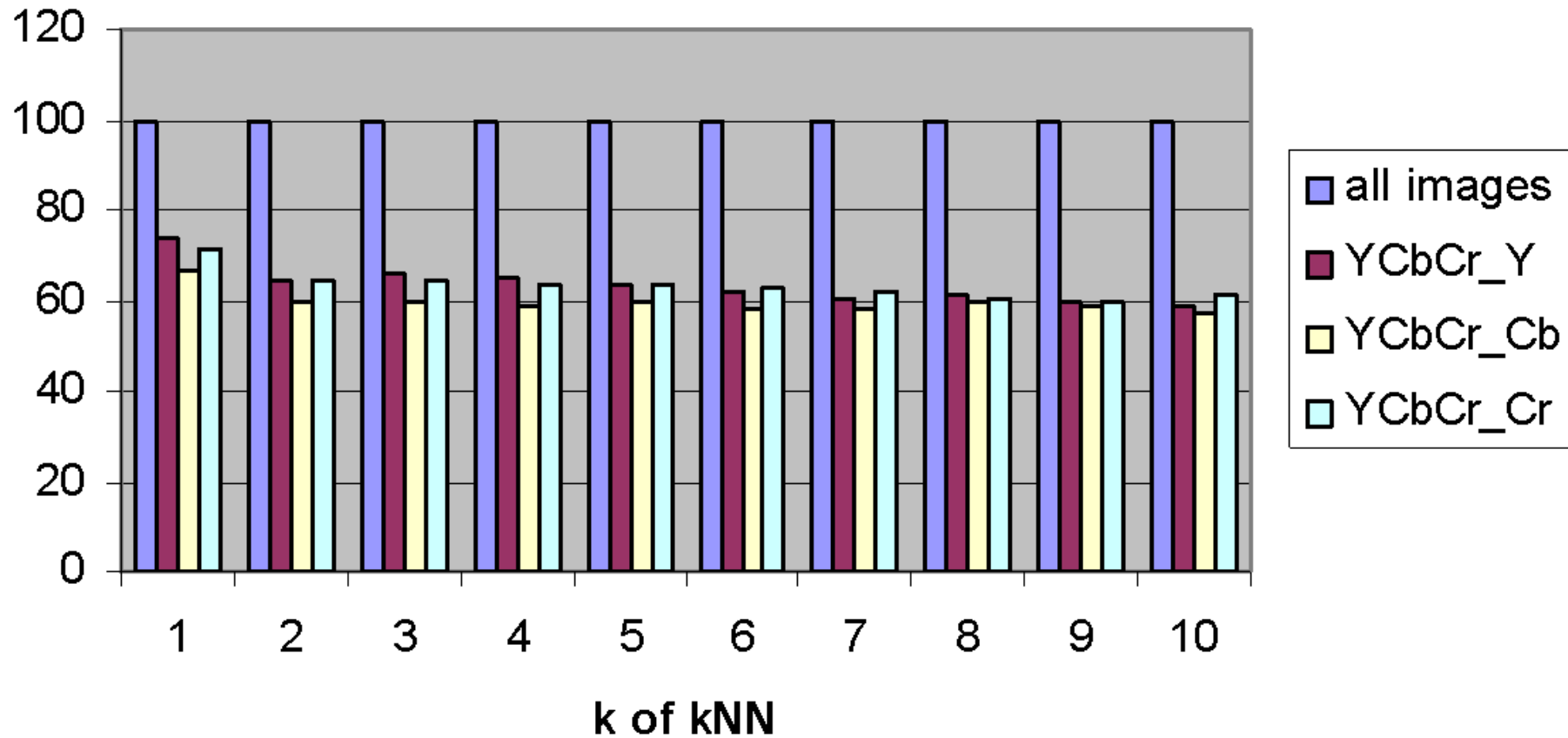
483 out of 484 images are used as training set, the remaining image is then classified to estimate the classification error (“leave-one-out” method). This process is repeated for each single image.

## Results: k-NN, 2 classes



Percentage of correctly classified images for co-occurrence histograms.

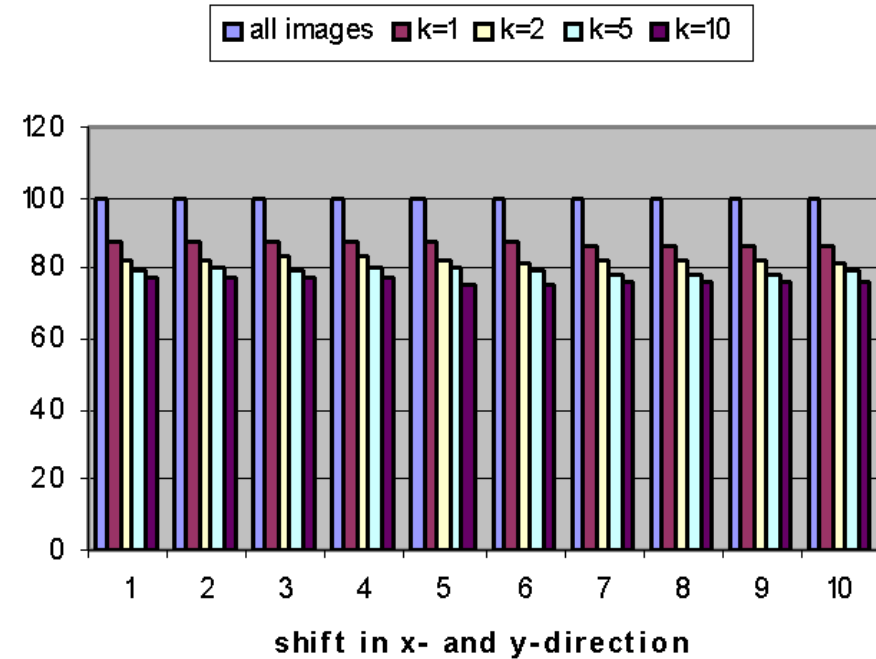
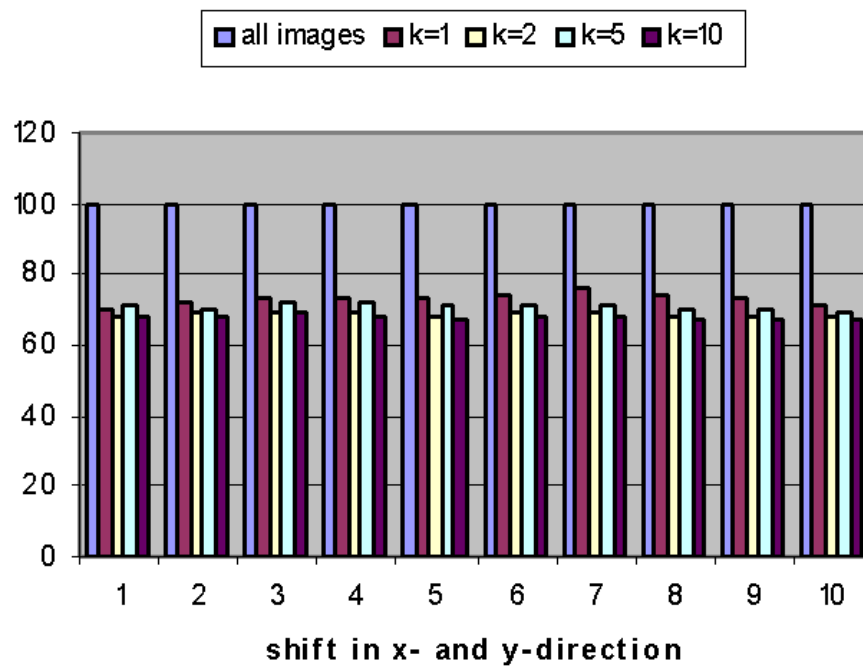
## Results: k-NN, 6 classes



Percentage of correctly classified images for co-occurrence histograms (YCrCb colourspace, 2 and 6 classes).

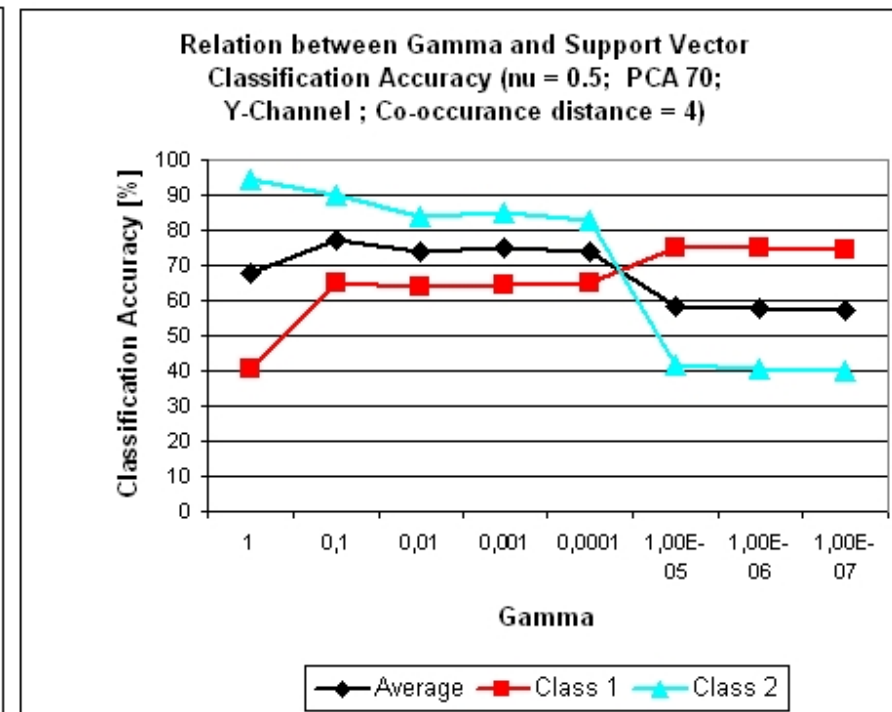
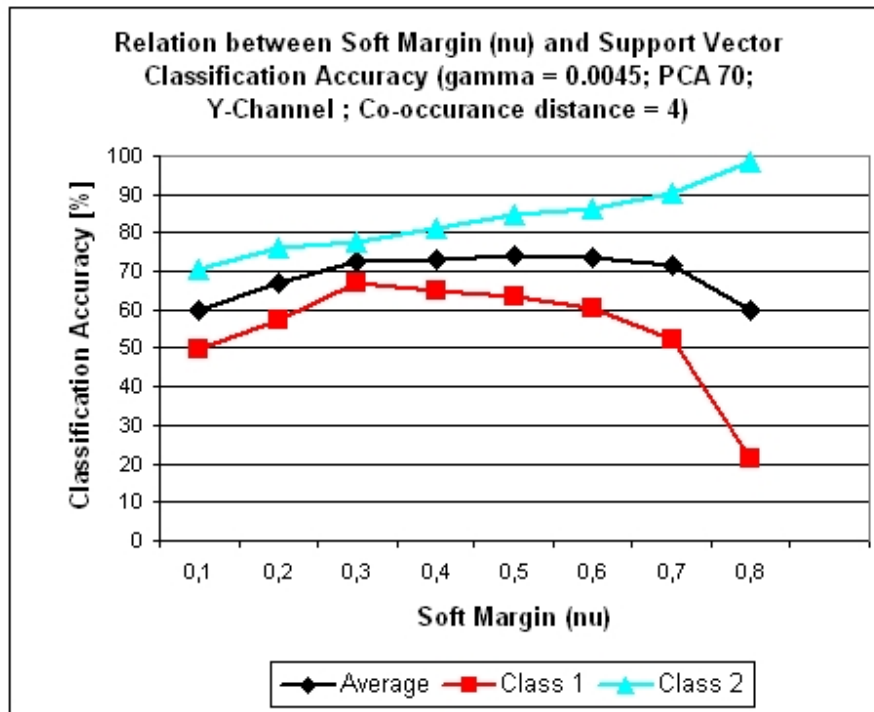


# Results: k-NN, Spatial Distance



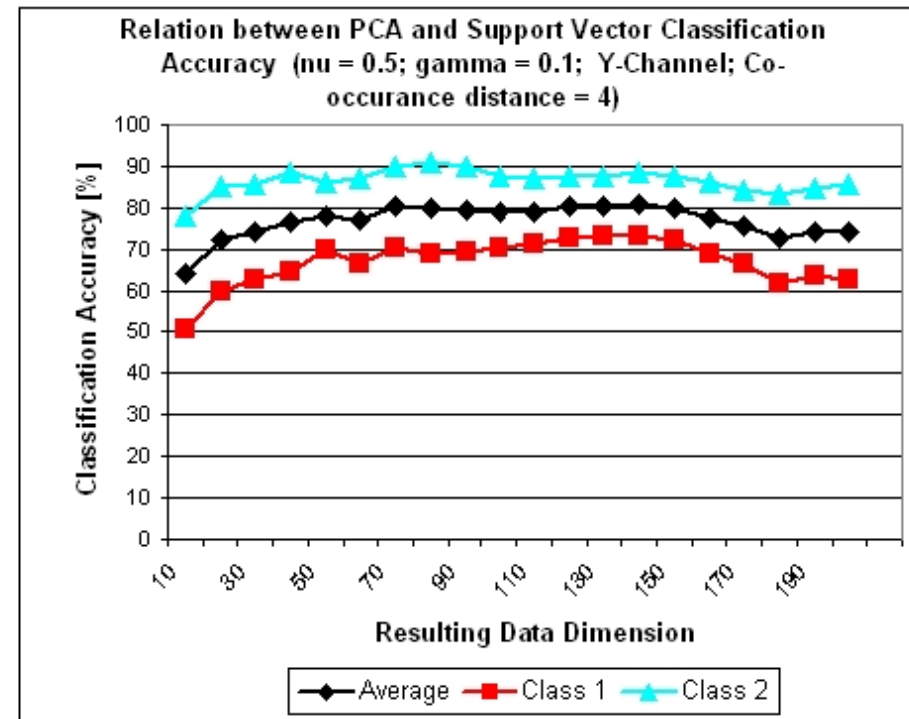
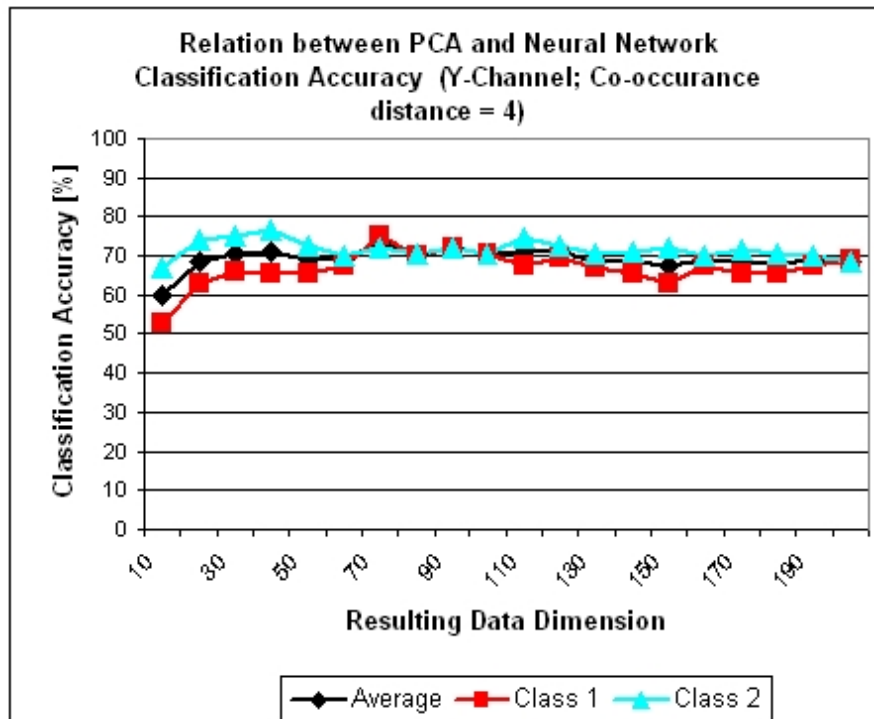
Percentage of correctly classified images for co-occurrence histograms (2 classes, G channel (RGB) and Y Channel (YCrCb))

# Results: SVM, Parameter Importance



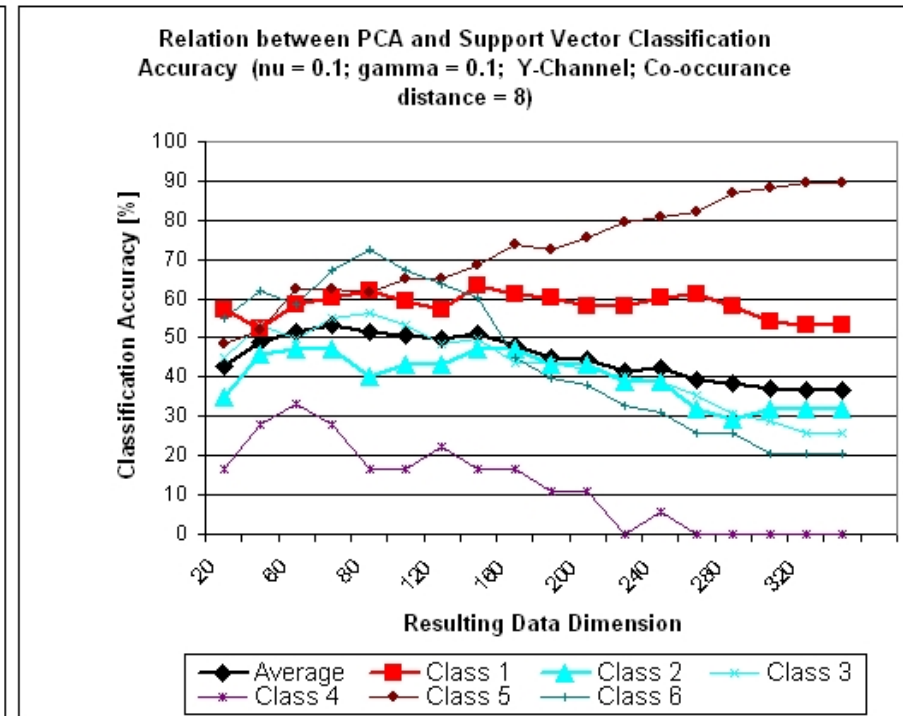
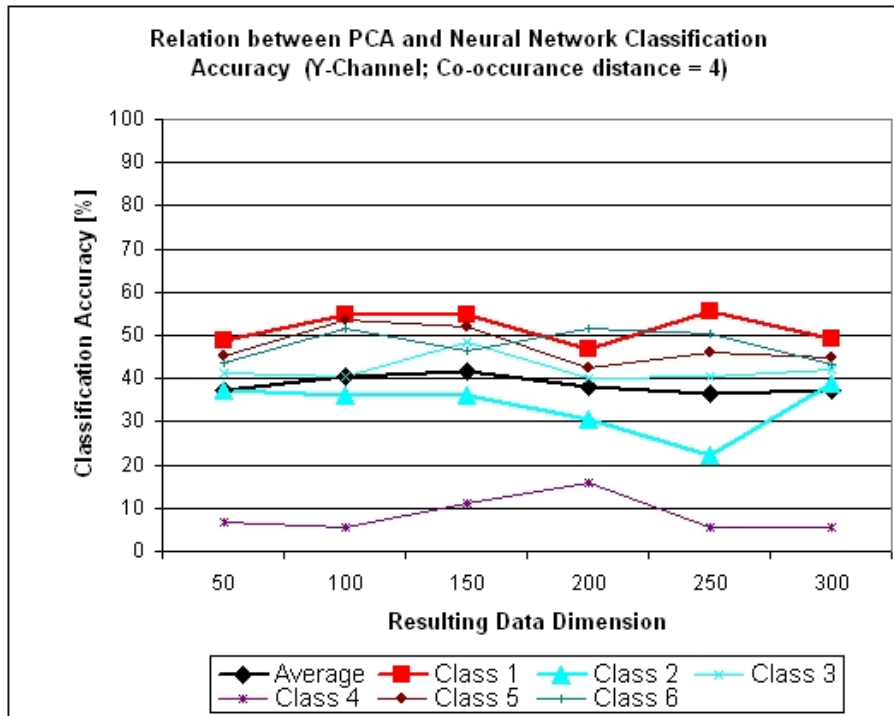
Percentage of correctly classified images for co-occurrence histograms (2 classes, Y-channel).

# Results: ANN & SVM – PCA dimensionality reduction I



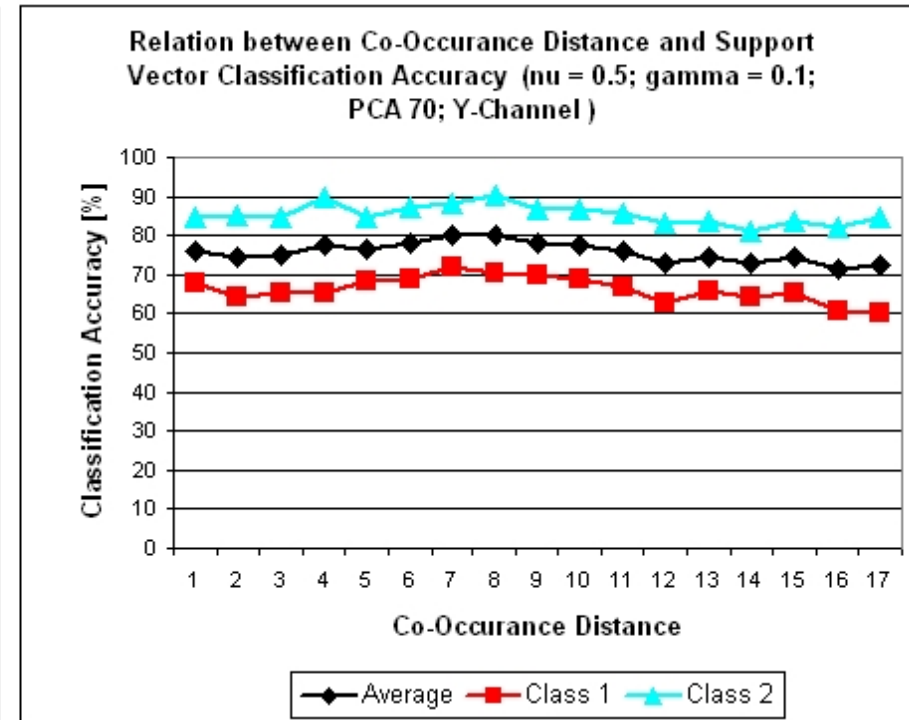
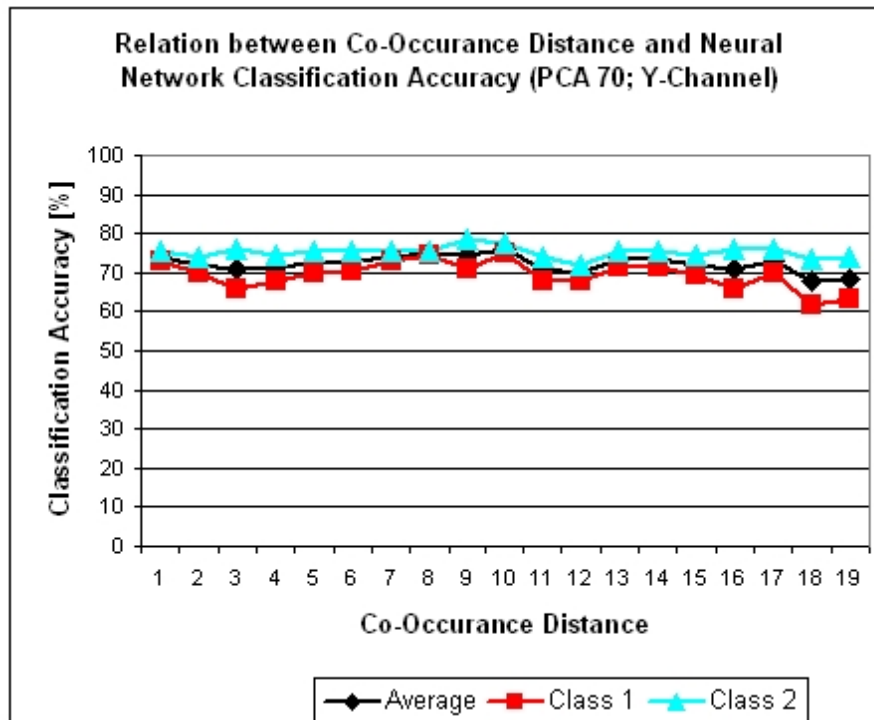
Percentage of correctly classified images for co-occurrence histograms (2 classes, Y-channel).

# Results: ANN & SVM – PCA dimensionality reduction II



Percentage of correctly classified images for co-occurrence histograms (6 classes, Y-channel).

# Results: ANN & SVM – Spatial Distance



Percentage of correctly classified images for co-occurrence histograms (2 classes, Y-channel).

## Conclusion

The results of our automated pit pattern classification system are encouraging but are meant to support but not to replace human observation. Especially false negatives of neoplastic lesions are of course a severe problem in potential clinical usage.

Interestingly, classification results of k-NN are clearly better as compared to ANN and SVM. This is probably due to the required dimensionality reduction for the latter two techniques. The spatial distance used in the co-occurrence histogram does not significantly influence the results.

In future work we will focus on “multimodal” schemes involving transform-based (e.g. Fourier, Wavelet and Gabor transform) and edge-based features as well to result in a multi-classifier system.

Thank you for your attention !

Questions ?