P. Perner, Image Mining: Issues, framework, a generic tool and its application to medical-image diagnosis, Journal Engineering Applications of Artificial Intelligence,vol. 15/3, pp. 193-203

Image Mining: Issues, Framework, a Generic Tool and its Application to Medical-Image Diagnosis

Abstract. A tool and a methodology for data mining in picture-archiving systems are presented. It is intended to discover the relevant knowledge for picture analysis and diagnosis from the database of image descriptions. Knowledge-engineering methods are used to obtain a list of attributes for symbolic image descriptions. An expert describes images according to this list and stores descriptions in the database. Digital-image processing can be applied to improve imaging of specific image features, or to get expert-independent feature evaluation. Decision-tree induction is used to learn the expert knowledge, presented in the form of image descriptions in the database. A constructed decision tree presents effective models of decision-making, which can be learned to support image classification by the expert. A tool for data mining and image processing is presented and its application to image mining is shown on the task of Hep-2 cell-image classification. However, the tool and the methodology are generic and can be used for other image-mining tasks. We applied the developed methodology of data mining in other medical tasks, such as in lung-nodule diagnosis in X-ray images, lymph-node diagnosis in MRI and investigation of breast MRI.

Keywords: Data Mining, Image Mining, Decision-Tree Induction, Knowledge Engineering, Interactive Image Analysis, Medical Image Mining, Image Classification

1 Introduction

Pictures, stored in picture-archiving and communication systems (PACS) [1] or other image-data bases [2], provide new possibilities for a deep study of specific and temporal features of the image object, such as for e.g. lesion in medical images and for a dynamical study of the feature evolution. That's why further development of a computer-assisted diagnosis is associated with the use of new intelligent capabilities such as data mining, which allow discovering the relevant knowledge for image analysis and diagnosis from the database of image descriptions. The application of data mining will help to get some additional knowledge about specific features of different classes and the way in which they are expressed in the image. This method can elicit non-formalized expert knowledge; it can automatically create effective models for decision-making, and can help to find some inherent non-evident links between classes and their imaging in the picture. It can help to get some nontrivial conclusions and predictions on the base of image analysis. The new knowledge obtained as a result of data analysis in the database can enhance the professional knowledge of the expert or the user of the image data base. This knowledge can also be used for teaching novices or can support image analysis and diagnosis by the expert.

An additional advantage of data mining application for the decision of medical or other tasks is on the long-run the opportunity for creation of fully automatic image-diagnosis systems that could be very important and useful in the case of lack of knowledge for decision-making.

In this paper we present our methodology for performing data mining on image data bases. In Section 2 we describe the recent state of the art in image mining and the problems concerned with image mining. A design of image-mining tools is considered in Section 3. The developed tool for image mining is presented in Section 4. A methodology for data mining that has been created and tested in the task of Hep-2 cell analysis is described in Section 5. Finally, in Section 6, we summarize our experience in applications of data-mining methodology in different medical tasks, such as pre-clinical diagnosis of peripheral lung cancer on the basis of lung tomograms, lymph-node diagnosis and investigation of breast diseases in MRI. Conclusions and plans for future work are given in Chapter 7.

2 Background

As shows the analysis of the literature, most of the recent work on image mining is devoted to knowledge discovery, such as clustering and mining association rules. They are dealing with the problem of searching the regions of special visual attention or interesting patterns in a large set of image, e.g. in CT and MRI image sets [3], [4] or in satellite images [5]. Usually experienced experts have discovered this information. However, the amount of images, which is being created by modern sensors, makes necessary the development of methods that can decide this task for the expert. Therefore, standard primitive features that are able to describe the visual changes in the image background are being extracted from the images and the significance of these features is being tested by a sound statistical test [3], [5]. Clustering is applied in order to explore the images seeking for similar groups of spatial connected components [6] or similar groups of objects [4]. Association rules are used for finding significant pattern in the images [5].

The measurement of image features in these regions or patterns gives the basis for pattern recognition and image classification. Computer-vision researches are fulfilled to create proper models of objects and scenes, to obtain image features and to develop decision rules that allow one to analyze and interpret the observed images. CAD methods of image processing, segmentation, and feature measurements are successfully used for this purpose [7], [8], [9]. The mining process is done bottom-up. As many numerical features as possible are extracted from the images, in order to achieve the final goal - the classification of the objects [10][11]. However, such a numerical approach usually does not allow the user to understand the way in which the reasoning process has been done.

The second approach to pattern recognition and image classification is an approach based on the symbolical description of images [26] made by the expert [12]. This approach can present to the expert in the explicit form the way in which the image has been interpreted. The experts having the domain knowledge usually prefer the second approach.

Usually simple numerical features are not able to give a description of complex objects and scenes. They can be described by an expert with the help of non-formalized symbolical descriptions, which reflect some gestalt in the expert domain knowledge. A problem is how to find out the relevant descriptions of the object (or the scene) for its interpretation, and how to construct a proper procedure for extraction of these features. This top-down approach is the more practical approach for most applications. However, the symbolical description of images and feature estimation face numerous difficulties:

1. A skilled expert knows how to interpret the image, but often he has no well-defined vocabulary to describe the objects, visual patterns and gestalt variances, which are standing behind his diagnostic decisions. When the expert is asked to make this knowledge explicit, he/she usually cannot specify and verbalize it.

2. Although numerous efforts are going on to develop such a vocabulary for specific medical tasks (for example, the ACR-BIRADS-code has been constructed for image analysis in mammography), the problem of difference between "displaying and naming" still exists.
3. A developed description language will differ for example from medical school to medical school, as a result the obtained symbolical description of image features by a human will be expert-dependent and subjective.
4. Besides this, the developed vocabulary usually consists of a large number of different symbolical features (image attributes) and feature values. It is not clear a-priori whether all the attributes, included into the vocabulary, are necessary for the diagnostic reasoning process. To select the necessary and relevant features would make the reasoning process more effective.

We propose a methodology of data mining that allows one to learn a compact vocabulary for the description of objects and to understand how this vocabulary is used for diagnostic reasoning. Besides that we also use basic image features that have been calculated from the image. This methodology can be used for a wide range of image-diagnostic tasks.

Developed methodology takes into account the recent status of the art in image analysis and feature extraction and combines it with new methods of data mining. It allows us to extract quantitative information from the image when it is possible, to combine it with subjectively determined diagnostic features, and then to mine this information for the relevant diagnostic knowledge acquisition by objective methods such as data mining.

Our methodology should help to solve some cognitive, theoretical and practical problems:

1. It will reproduce and display a decision model of an expert for specific task solutions.
2. It will show the pathway of human reasoning and classification. Image features, which are basic for correct decision by the expert, will be discovered.
3. A developed model will be used as a tool to support the decision-making of a physician who is not an expert in a specific field of knowledge. It can be used for teaching novices.

The application of data mining will help to get some additional knowledge about specific features of different classes and the way in which they are expressed in the image. It could help to find some inherent non-evident links between classes and their imaging in the picture that could be used to make some nontrivial conclusions and predictions on the base of elicited knowledge.

3 Design Considerations

We developed a tool for data mining, which could meet several requests:

1. The tool has to be applicable for a wide range of image-diagnostic tasks and image modalities that occur for example in the radiological practice.
2. It should allow the users to develop their own symbolic descriptions of images in the terms which are appropriate to the specific diagnostic task.
3. Users could have a possibility for updating or adding features according to new images or a diagnostic problem.
4. It should support the user in the analysis and interpretation of images; for example in the evaluation of new imaging devices and radiographic materials.

Taking into account these criteria and the recent state-of-the-art in image analysis, we provided an opportunity for semiautomatic image processing and analysis to enhance imaging of diagnostically important details in the image and to measure some image features directly in the image and by this way to support the user by the analysis of images. The user has to have the possibility to interact with the system in order to adapt the results of image processing.

This image-processing unit should provide extraction of such low-level features as blobs, regions, ribbons, lines, and edges. On the basis of these low-level features we are able to calculate then some high-level features to describe the image. Besides that, the image-processing unit should allow evaluation of some statistical image properties, which might give valuable information for the image description.

However, some diagnostically important features, such as "irregular structure inside the nodule", “tumor” are not so-called low-level features. They present some gestalts of expert domain knowledge. Development of an algorithm for extraction of such image features can be a complex, or even unsolvable problem. So, we identify different ways of representing the contents of an image that belongs to different abstraction levels (see Figure 1). We can describe an image:

- by statistical properties; that is the lowest abstraction level;
- by low-level features and their statistical properties such as regions, blobs, ribbons, edges and lines. This is the next higher abstraction level;
- by high-level or symbolic features that can be obtained from the low-level features;

- and, finally, by expert symbolic description, which is the highest abstraction level.

The image-processing unit combined with the data-evaluation unit should allow a user to learn the relevant diagnostic features and effective models for the image interpretation. Therefore, the system as a whole should meet the following criteria:

1. Support the medical person as much as possible by the extraction of the necessary image details (region of interest).
2. Fulfill measurement of the feature values directly in the image, when it is possible.
3. Display the interesting image details to the expert.
4. Store in a database the measured feature values as well as the subjective description of images by the expert.
5. Import these data from the database into the data-mining unit.

4 System Description

Figure 2 shows a scheme of the tool for image mining. There are two parts in the tool: the unit for image analysis, feature extraction, and storage of image descriptions (Fig. 3) and the unit for data mining (Fig. 4).

Both units are written in C++ and run under Windows95 and Windows NT. These two units communicate over a database of image descriptions, which is created in the frame of the image-processing unit. This database is the basis for the data-mining unit (Fig. 4).

An image from the image archive is selected by the expert and then it is displayed on a monitor (Fig. 3). To perform image processing an expert communicates with a computer. He/she determines whether the whole image or part of it have to be processed and outlines an area of interest (for example, a nodule region) with an overlay line. The expert can calculate some image features in the marked region (object contour, square, diameter, shape, and some texture features) [13]. The expert evaluates or calculates image features and stores their values in a database of image features. Each entry in the database presents features of the object of interest. These features can be numerical (calculated on the image) and symbolical (determined by the expert as a result of image reading by the expert). In the latter case the expert evaluates object features according to the attribute list, which has to be specified in advance for object description. Then he/she feeds these values into the database.

When the expert has evaluated a sufficient number of images, the resulting database can be used for the mining process. The stored database can easily be loaded into the data mining tool *Decision Master* (Fig. 4).

The *Decision Master* fulfills a decision-tree induction that allows one to learn a set of rules and basic features necessary for decision-making in a specified diagnostic task. The induction process does not only act as a knowledge discovery process, it also works as a feature selector, discovering a subset of features that is the most relevant to the problem solution.

Decision trees partition decision space recursively into sub-regions based on the sample set. By this way the decision trees recursively break down the complexity of the decision space. The outcome has a format which naturally presents the cognitive strategy that can be used for the human decision-making process.

For any tree all paths lead to a terminal node, corresponding to a decision rule that is a conjunction (AND) of various tests. If there are multiple paths for a given class, then the paths represent disjunctions (ORs) [14].

The developed tool allows choosing different kinds of methods for feature selection, feature discretization, pruning of the decision tree and evaluation of the error rate. It provides an entropy-based measure, a gini-index, gain-ratio and chi square method for feature selection [15].

The *Decision Master* provides the following methods for feature discretization: cut-point strategy, chi-merge discretization, minimum description length, principal based discretization method and lvq-based method [15]. These methods allow one to make discretization of the feature values into two and more intervals during the process of decision-tree building. Depending on the chosen method for attribute discretization, the result will be a binary or n-ary tree, which will lead to more accurate and compact trees.

The *Decision Master* allows one to chose between cost-complexity pruning, error-reduction-based methods and pruning by confidence-interval prediction. The tool also provides functions for outlier detections.

To evaluate the obtained error rate one can choose test-and-train and n-fold cross validation. Missed values can be handled by different strategies [15].

The user selects the preferred method for each step of the decision tree induction process. After that the induction experiment can start on the acquired database. A resulting decision tree will be displayed to the user. He/she can evaluate the tree by checking the features used in each node of the tree and comparing them with his/her domain knowledge.

Once the diagnosis knowledge has been learnt, the rules are provided either in txt-format for further use in an expert system or the expert can use the diagnosis component of the *Decision Master* for interactive work. It has a user-friendly interface and is set up in such a way that non-computer specialists can handle it very easily.

5. The Overall Image Mining Procedure

The whole procedure for image mining is summarized in Fig. 5. It is partially based on our developed methodology for image-knowledge engineering [16]. The process can be divided into five major steps: 1. Brain storming, 2. Interviewing Process 3. Collection of Image Descriptions into the Data Base, 4. Mining Experiment, and 5. Review.

Brain storming is the process of understanding the problem domain and identifying the important knowledge pieces on which the knowledge-engineering process will focus.

For the interviewing process we used our developed methodology for image-knowledge engineering described in [16] in order to elicit the basic attributes as well as their attribute values. Then the proper image processing and feature-extraction algorithms are identified for the automatic extraction of the features and their values.

Based on these results we then collected into the data base image readings done by the expert and done by the automatic image analysis and feature-extraction tool. The resulting data base is the basis for our mining experiment. The error rate of the mining result was then determined based on sound statistical methods such as cross validation. The error rate as well as the rules were then reviewed together with the expert and depending on the quality of the results the mining process stops or goes into a second trail, starting either at the top with eliciting new attributes or at a deeper level, e.g. with reading new images or incorporating new image-analysis and feature-extraction procedures. The incorporation of new image-analysis and feature-extraction procedures seems to be an interactive and iterative process at the moment, since it is not possible to provide ad-hoc sufficient image-analysis procedures for all image features and details appearing in the real world [17]. The mining procedure stops as soon as the expert is satisfied by the results.

6 A Case Study

6.1 The Application

We will describe the usage of the image mining tool based on the task of HEp-2 cell classification. HEp-2 cells are used for the identification of antinuclear autoantibodies (ANA). They allow the recognition of over 30 different nuclear and cytoplasmic patterns which are given by upwards of 100 different autoantibodies. The identification of these patterns has up to now been done manually by a human inspecting the slides with the help of a microscope. The lacking automation of this technique has resulted in the development of alternative techniques based on chemical reactions, which have not the discrimination power of the ANA testing. An automatic system would pave the way for a wider use of ANA testing.

Recently, the various HEp-2 cell images occurring in medical practice are being collected into a data base at the university hospital of Leipzig. The images were taken by a digital image-acquisition unit consisting of a microscope AXIOSKOP 2 from Carl Zeiss Jena, coupled with a color CCD camera Polariod DPC [19]. The digitized images were of 8-bit photometric resolution for each color channel with a per pixel spatial resolution of 0.25 μm. Each image was stored as a color image on the hard disk of the PC but is transformed into a gray-level image before used for automatic image analysis.

The scope of our work was to mine these images for the proper classification knowledge so that it can be used in medical practice for diagnosis or for teaching novices. Besides that it should give us the basis for the development of automatic image diagnosis system.

Our experiment was supported by an immunologist who is an expert in the field and acts as a specialist to other laboratories in case of diagnostically complex cases.

6.2 Brainstorming and Image Catalogue

First, we started with a brain storming process that helped us to understand the expert´s domain and to identify the basic pieces of knowledge. We could identify mainly four pieces of knowledge: 1. Hep-2 cell atlas [18], the expert, slide preparation and a book describing the basic parts of a cell and their appearance.

Then the expert collected prototype images for each of the six classes appearing most frequently in his daily practice. The expert wrote down a natural-language description for each of these images. As a result we obtained an image catalogue having a prototype image for each class and associated to each image is a natural-language description of the expert (see Fig. 6).

6.3 Interviewing Process

Based on these image descriptions we started our interviewing process. First, we only tried to understand the meaning of the expert description in terms of image features. We let him circle the interesting object in the image to understand the meaning of the description. After having done this, we went into a structured interviewing process asking for specific details such as: “Why do you think this object is *fine-speckled* and the other one is not. Please describe the difference between these two." It helped us to verify the expert description and to make the object features more distinct.

Finally, we could extract from the natural-language description the basic vocabulary (attributes and attribute values, see table 1) and associate the meaning to each attribute.

In a last step we reviewed the chosen attributes and the attribute values with the expert and found a common agreement on the chosen terms. The result was an attribute list which is the basis for the description of object details in the images. Furthermore, we identified from the whole set of feature descriptors our image-analysis tool provides the set of a feature descriptors which might be useful for the objective measurement of image features. In our case we found that describing the cells by their boundary and calculating the size and the contour of the cell might be appropriate. The different descriptors of the nuclei of the cells might be sufficiently described by the texture descriptor of our image-analysis tool.

6.4 Collection of Image Descriptions into the Data Base

Now we could start to collect a data base of image descriptions based on these attributes and attribute values as well as on feature measurements calculated with the help of the image-analysis tool. For our experiment we used a data set of 110 images. The data set contained 6 classes, each equally distributed. For each class we had 20 images. The expert used the image-analysis tool shown in Fig. 3 and displayed one after another each image from our data base. He watched the images on display and described the image content on the basis of our attribute list and fed the attribute values into the data base. Besides that he marked the objects of interest in the image on display and used the necessary feature descriptors selected during the interviewing process and provided by the image-analysis unit to measure the image features such as size, contour, and texture. The resulting values for these features are automatically fed into the data base and stored together with the expert's image description into the data base (see Fig. 7).

6.5 The Image Mining Experiment

The collected data set was then given to the data-mining tool *Decision-Master*. The decision-tree induction algorithm that showed the best results on this data set is based on the entropy-criterion for the attribute selection, cut-point strategy for the attribute discretization and minimal error-reduction pruning. We carried out three experiments. First, we learnt a decision tree only based on the image reading by the expert, then learnt a decision tree only based on the automatic calculated images features, and finally, we learnt a decision tree based on a data base containing both feature descriptions. The resulting decision tree for the expert's reading is shown in Figure 8 and the resulting decision tree for the expert's reading together with the measured image features is shown in Figure 9. We do not show the tree for the measured image features, since the tree is too complex. The error rate was evaluated by leave-one-out cross-validation.

The error rate of the decision trees from the first two experiments is higher than the error rate made by the expert (see table 2). None of the trees whether based on the expert's reading or based on the measured image features give a sufficiently low error rate. Only the combined data base from the expert's reading and measured image features gives us an error rate that comes close to expert's error rate.

6.6 Review

The tree created based on the image readings from the expert has an error rate of 27,9% (see table 2). Under the assumption that the class labels represent the true class (gold standard), we can only conclude that there is a knowledge gap. There must be some hidden knowledge which the expert is using during decision making, but she could not make this knowledge explicit during the interviewing process. Here we have an example for the problem "difference between showing and naming" mentioned in Section 2. However, the expert's error rate is also high.

Our first objection was: Is the assumption that the class label is the true class label true or not? As far as we know the chemical investigation of the serum which was used to determine the gold standard does not so accurately discriminate between the different classes.

The experiment based on the features automatically measured in the images gives us no better results. The resulting tree is very bushy and deep and uses almost all attributes.

Only the combination between the expert's readings and the readings by the image-analysis unit shows us reasonable results. The feature nucleoli is the most important feature and the correct description of the nucleoli will improve the results dramatically. During the image-analysis phase we did not describe this object separately. The hope was that the texture descriptor for the whole cell is sensitive enough to model the different visual appearances of the different cells. The experiment shows that only the combination of basic image descriptors from the image analysis with expert reading gave sufficient results. Therefore, we believe that our first objection on the true class label does not hold any more. We rather that think in order to improve the accuracy of the classifier we must find a good feature descriptor for the different appearances of the object nucleoli.

7 Lessons Learned

We have found out that our methodology of data mining allows a user to learn the decision model and the relevant diagnostic features. A user can independently use such a methodology of data mining in practice. He/she can easily perform different experiments until he/she is satisfied with the result. By doing that he/she can explore his/her application and find out the connection between different knowledge pieces.

However some problems should be taken into account for the future system design.

As we have already pointed out in a previous experiment [24], an expert tends to specify symbolical attributes with a large number of attribute values. For e.g. in this experiment [24] the expert specified for the attribute "margin" fifteen attribute values such as "non-sharp", "sharp", "non-smooth", "smooth", and so on. A large number of attribute values will result in small sub-sample sets soon after the tree-building process started. It will result in a fast termination of the tree-building process. This is also true for small sample sets that are usual for medicine. Therefore, a careful analysis of the attribute list should be done after the physician has specified it.

During the process of building the tree, the algorithm picks the attribute with the best attribute-selection criteria. If two attributes have both the same value, the one that appears first in the attribute list will be chosen. That might not always be the attribute the expert would choose himself. To avoid this problem, we think that in this case we should allow the expert to choose manually the attribute that he/she prefers. We expect that this procedure will bring the resulting decision model closer to the expert's ones.

The developed image-analysis tool allows only to extract a few image features so far (see Sect. 4). However, it supported the analysis and exploration of other image-diagnosis tasks, such as the analysis of sheep follicle and lymph nodule analysis. New applications might require further feature descriptors. Therefore the image-analysis tool must have an open architecture that allows to incorporate new feature descriptors into the tool.

The described method of image mining had been already established in practice. It runs at the University hospital in Leipzig and Halle and at the Veterinary department of the University in Halle, where the method is used for analysis of sheep follicle based on a texture descriptor, evaluation of imaging effects of radiopaque material for lymph-nodule analysis, mining knowledge for IVF therapy, transplantation medicine and for the diagnosis of breast carcinoma in MR images. In all these tasks we did not have a well-trained expert. These were new tasks and reliable decision knowledge has not been built up in practice yet. The physicians did the experiments by themselves. They were very happy with the obtained results, since the learnt rules gave them deeper understanding of their problems and helped to predict new cases. It helped the physicians to explore their data and inspired them to think about new improved ways of diagnosis.

8 Conclusion and Further Work

In this paper we presented our methodology of data mining in picture-archiving systems. The basis for our study is a sufficiently large database with images and expert descriptions. Such databases result for example from the broad use of picture archiving systems in medical domains.

We were able to learn the important attributes needed for image interpretation and to understand the way in which these attributes were used for decision-making by applying data-mining methods to the database of image descriptions. We showed how the domain vocabulary should be set up in order to get good results, and which techniques should be used in order to check reliability of the chosen features.

The explanation capability of the induced tree was reasonable. The attributes included into the tree represented the expert knowledge.

Finally, we can say that picture-archiving systems in a combination with data-mining methods open a possibility of advanced computer-assisted diagnosis-system development. However, it will not give the expected result if the PACS have not been set up in the right way. Pictures and experts' descriptions have to be stored in a standard format in the system for further analysis. Since standard vocabulary and very good experts are available for many medical diagnosis tasks, this should be possible. What is left is to introduce this method to the medical community, which we have done recently for mammogram analysis and lymph nodule diagnosis. Unfortunately, it is not possible to provide image-analysis systems, which can extract features for all kind of images. Often it is the case that it is not clear how to describe a particular feature by automatic procedures developed for image-feature extraction. The expert's description will still be necessary for a long time. However, once the basic discriminating features have been found, the result can lead in the long run to fully automatic image-diagnosis system, which is set up for a specific type of image diagnosis. In our future work we should like to extend the number of feature extractors to a larger number of necessary feature extractors.

Acknowledgements

Part of this work has been financed by the German Science Foundation under the grant number PE-501 and by the Germany Ministry of Economy under the grant LernBildZell IN 1052.

We should like to thank the medical expert Dr. Sack from the University of Leipzig for providing us the HEp2-cell images as well as for the expert analysis and description of medical images.

References

1. Andriole, K. P.: Anatomy of Picture archiving and communication systems: Nuts and Bolts-Image Acquisition: getting digital images from imaging modalities. J. of Digital Imaging**,** Vol. 12, 2, Suppl. 1 (2000) 216-217.
2. Nagy, G. Image Database, Image and Vision Computing 3, 3, 111-117, 1986
3. Megalooikonomou, K., Davatzikos, C., Herskovits, E.: Mining lesion-defect associations in a brain image database, in Proc. Int. Conf. Knowledge Discovery and Data Mining (KDD`99), San Diego, California, August 1999, 347-351, 1999.
4. Eklund, P. W., You, J., Deer, P.: Mining remote sensing image data: an integration of fuzzy set theory and image understanding techniques for environmental change detection. In: Data Mining and Knowledge Discovery: Theory, Tools, and Technology. Belur V. Dasarathy (eds.). SPIE , Vol. 4057 (2000) 265-273.
5. Burl, M. C., Lucchetti, D.: Autonomous visual discovery. In: Data Mining and Knowledge Discovery: Theory, Tools, and Technology, Belur V. Dasarathy (eds.). SPIE, Vol. 4057 (2000) 240-250.
6. Zaiane, O. R., Han, J.: Discovery spatial associations in Image. In: Data Mining and Knowledge Discovery: Theory, Tools, and Technology. Belur V. Dasarathy (eds.), SPIE, Vol. 4057 (2000) 138-148.
7. Kehoe, A. and Parker, G.A.: An IKB defect classification system for automated industrial radiographic inspection. IEEE Expert Systems 8 (1991) 149-157.
8. Schröder, S., Niemann, H., Sagerer, G.: Knowledge acquisition for a knowledge based image analysis system. In*:* Proc. of the European Knowledge-Acquisition Workshop (EKAW 88). Bosse, J., Gaines, B. (eds.), GMD-Studien, Vol**.** 143, Sankt Augustin (1988).
9. Perner, P.: Case-Based Reasoning for the Low-level and High-level Unit of an Image Interpretation System. In: Advances in Patter Recognition. Singh S. (ed.). Springer-Verlag (1998) 45-54.
10. P. Perner, U. Zscherpel, and C. Jacobsen. A Comparison between Neural Networks and Decision Trees based on Data from Industrial Radiographic Testing. Pattern Recognition Letters, 2 (2001), pp 47-54.
11. Fischer S., Bunke H., Automatic Identification of Diatoms Using Decision Forests, In: P. Perner (ed.), Machine Learning and Data Mining in Pattern Recognition, Springer Verlag 2001, lnai 2123, p. 173-183.
12. P. Perner, Mining Knowledge in Medical Image Databases, In Data Mining and Knowledge Discovery: Theory, Tools, and Technology, Belur V. Dasarathy (eds.), Proceedings of SPIE Vol. 4057 (2000), 359-369

13. Zamperoni, P.: Feature Extraction, In:, Progress in Picture Processing, Eds. H. Maitre and J. Zinn-Justin. Elsevier Science (1996) 121-184.
14. Weiss, S.: Predictive Data Mining, Kluwer Verlag (1996).
15. Perner, P.: Data Mininig on Multimedia Data, Springer Verlag (2001) (to appear).
16. Perner, P. A.: Knowledge-based image inspection system for automatic defect recognition, classification, and process diagnosis. Int. J. on Machine Vision and Applications 7 (1994) 135-147.
17. G. Nagy, Personal Communication on Image Mining 2001
18. Bradwell, A.R., Stokes, R.P., Johnson, A.D., Atlas of Hep-2 patterns, The Binding Site Ltd., Birmingham 1995.
19. Sack, U. Digital Image Acquisition Unit for Fluorescent Images, IBaI Report 2000
20. Perner, P., Belikova, T. P., Yashunskaya, N. I. Knowledge Acquisition by symbolic decision tree induction for interpretation of digital images in radiology. In: Advances in Structural and Syntactical Pattern Recognition. Lecture Notes in Computer Science. Perner, P, Wang, P., Rosenfeld, A. (eds). Springer, Vol. 1121 (1996). 208-219.
21. Heywang-Köbrunner, S., Perner, P.: Optimized Computer-Assistet Diagnosis based on Data Mining, Expert Knowledge and Histological Verification. IBaI Report ISSN 1431-2360 (1998).
25. Data Mining Tool Decision Master. http://ww.ibai_solution.de .
26. Bischof; W.F., Caelli, T. Learning spatio-temporal relational structure, Applied Artificial Intelligence, Volume 15, Number 8, 2000, p. 707-722.

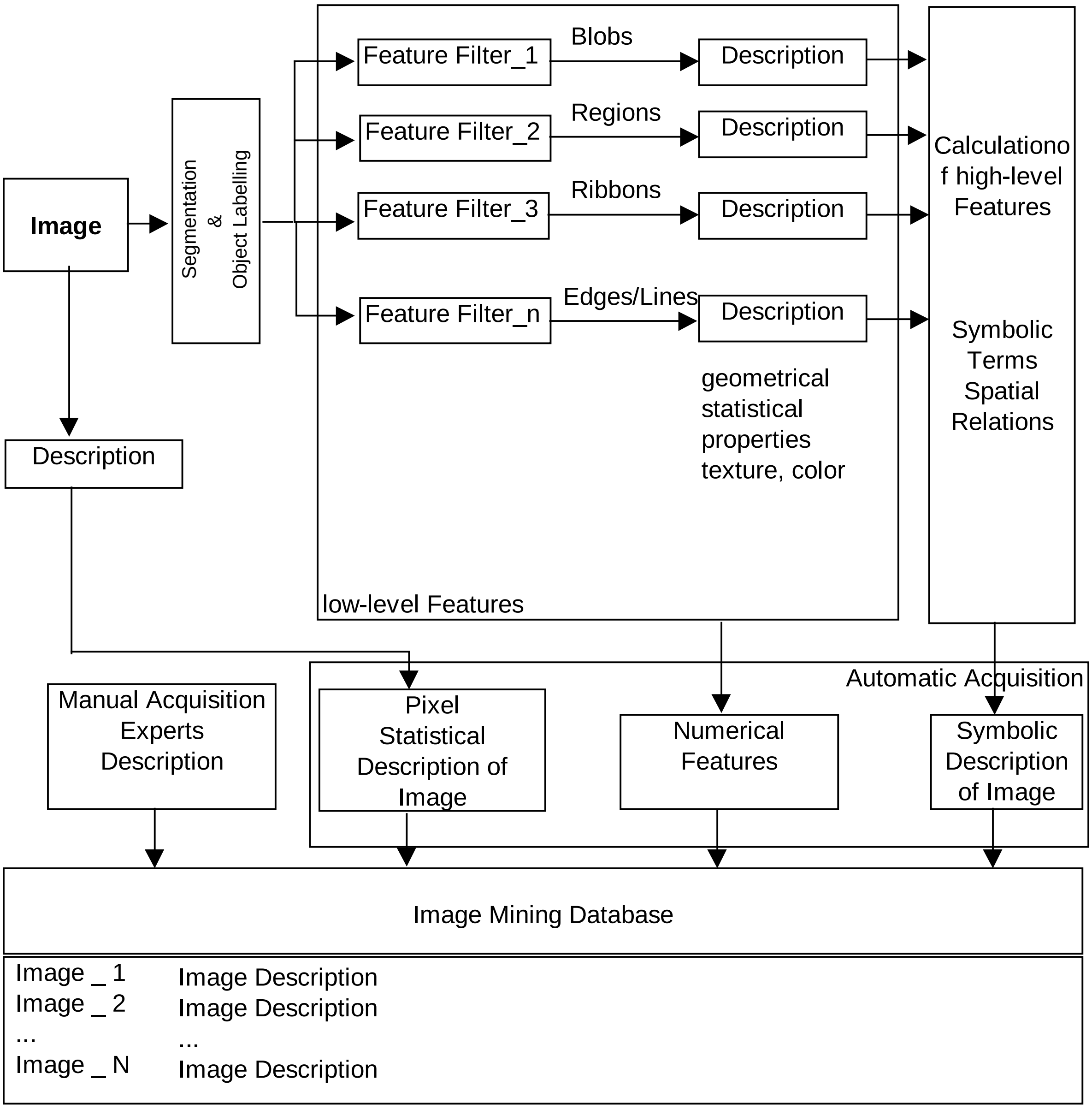


Figure 1 Overview on Image Descriptions based on different Abstraction Levels

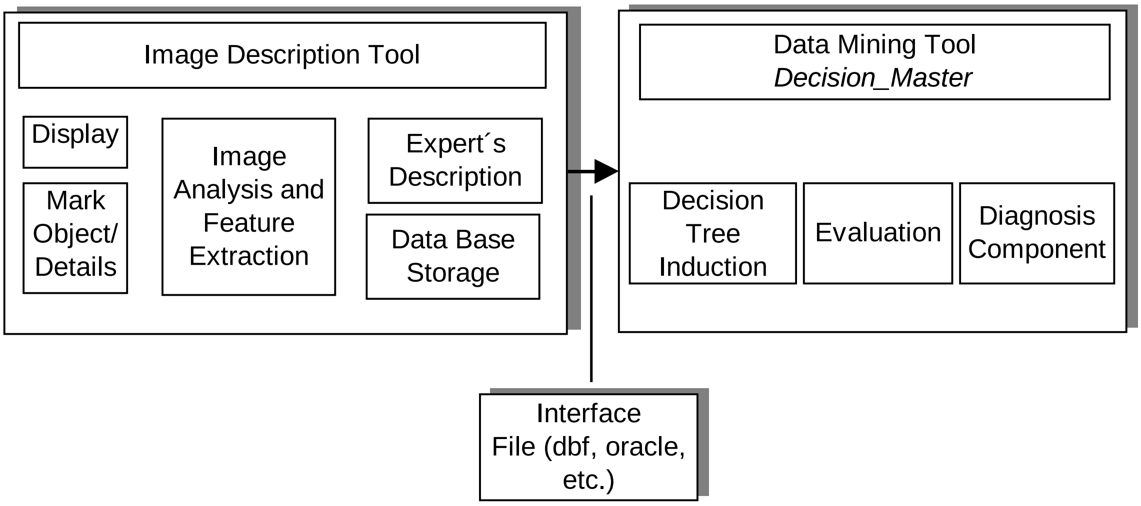
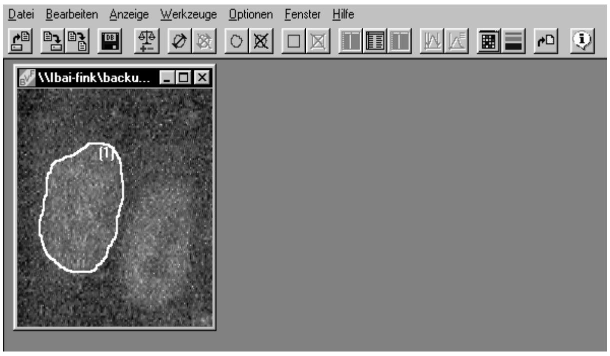
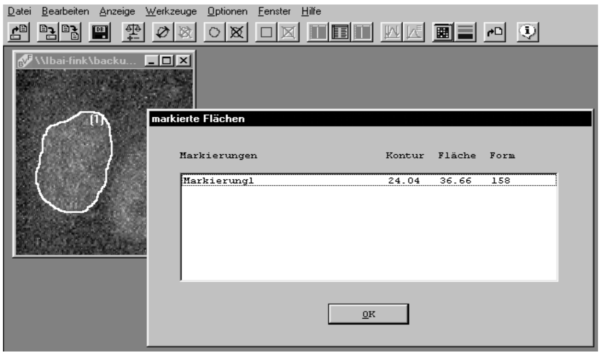


Figure 2 Architecture of an Image Mining Tool

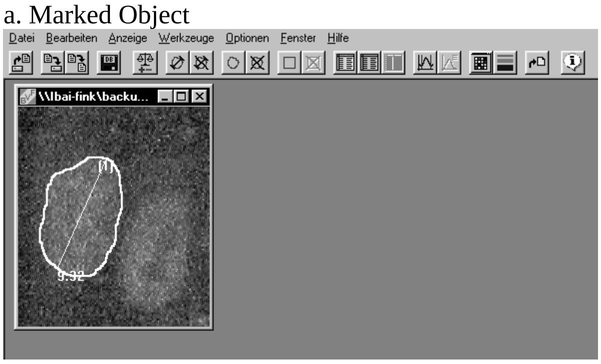
P. Perner, Image Mining: Issues, framework, a generic tool and its application to medical-image diagnosis, Journal Engineering Applications of Artificial Intelligence,vol. 15/3, pp. 193-203

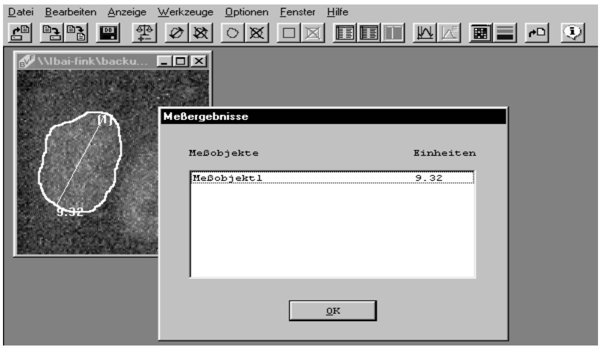




a. Marked Object

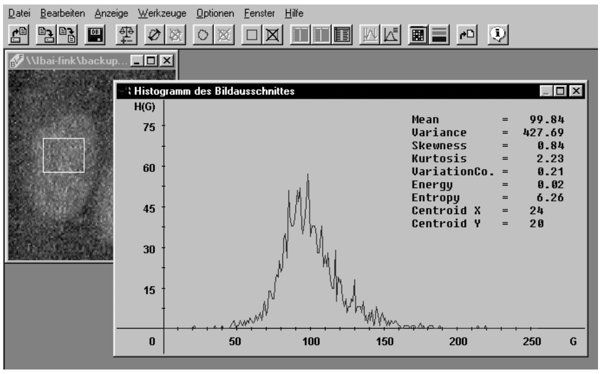
b. Contour and Area calculated from Marked Object

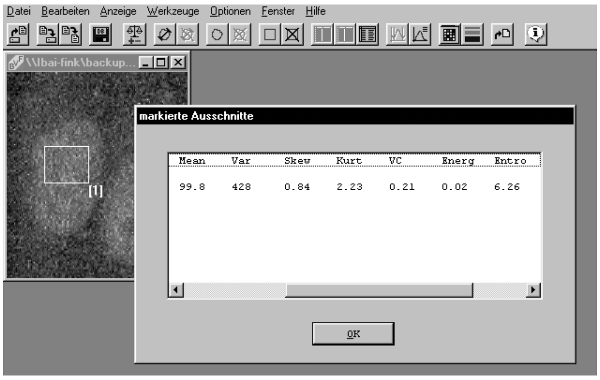




c. Marked Diameter

d. Measurement of Diameter





e. Histogram and measured Texture Values

f. Data Base Entry of Texture Features

Fig. 3 a-f Image Analysis Unit for the Extraction of the Image Descriptions

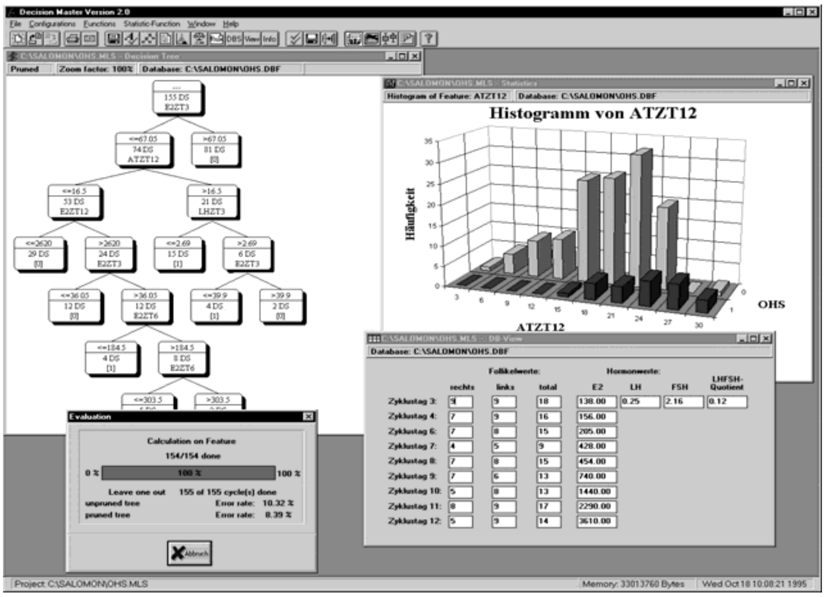


Figure 4 Data Mining Tool Decision Master

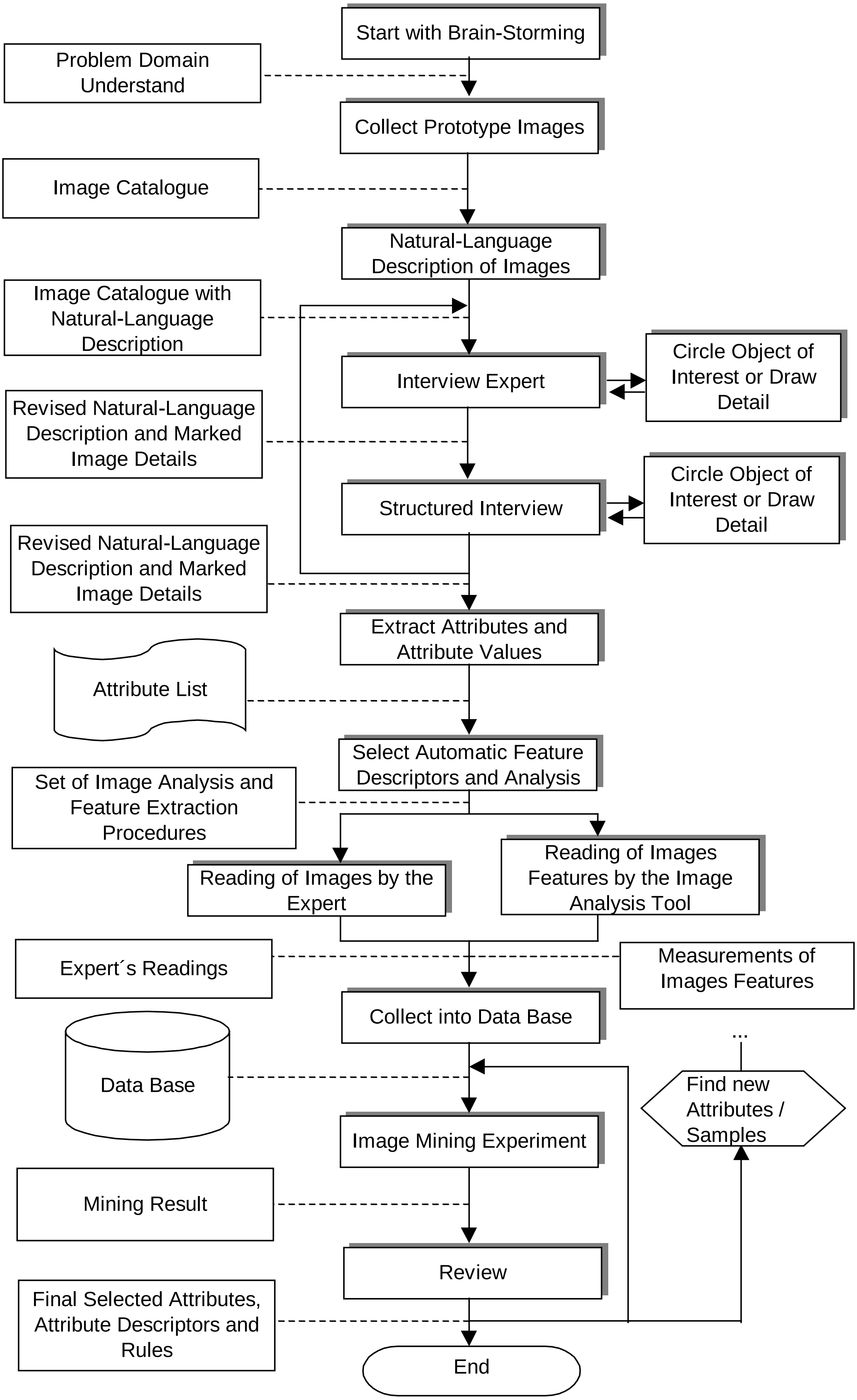


Figure 5 Procedure of the Image Mining Process

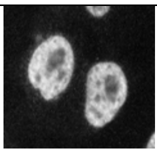
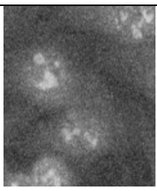
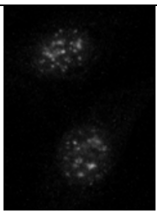
Class	**Image**	**Description**
Fine Speckled 200 000		Smooth and uniform fluorescence of the nuclei Nuclei sometimes dark Chromosomes fluoresced weak up to extreme intensive
Fine dotted (speckled) nuclei fluorescence 320 200		Dense fine speckled fluorescence Background diffuse fluorescent
Homogeneous Nuclear 100 000		A uniform diffuse fluorescence of the entire nucleus of interphase cells. The surrounding cytoplasm is negative.
...	...	...
Centromere 500 000		Nuclei weak uniform or fine granular, poor distinction from background

Figure 6 Image Catalogue and Expert´s Description

P. Perner, Image Mining: Issues, framework, a generic tool and its application to medical-image diagnosis, Journal Engineering Applications of Artificial Intelligence,vol. 15/3, pp. 193-203

Class	Contour (Kontur)	Area	Shape Factor (Form)	MEAN	VAR	SKEW	CURT	VC	ENERGY	...	NUCLEOLI	CHROMO	CYTOPLA (Zytopla)	Background (Hintergrund)
100000	14,3734	14,3189	144,2812	87,1507	244,3043	1,1233	7,5139	0,1793	0,0209	...	1	1	0	1
100320	10,3675	7,2986	147,2687	144,6974	282,0444	-0,6999	2,4243	0,1161	0,0238	...	1	0	0	0
320200	11,9142	9,4348	150,4512	132,5286	675,6562	0,1685	-0,5039	0,1961	0,0119	...	2	0	0	1
200000	9,0332	5,2114	156,5795	94,5199	1400,9983	0,6564	-0,3728	0,3960	0,0100	...	2	0	0	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure 7 Excerpt from Data Base

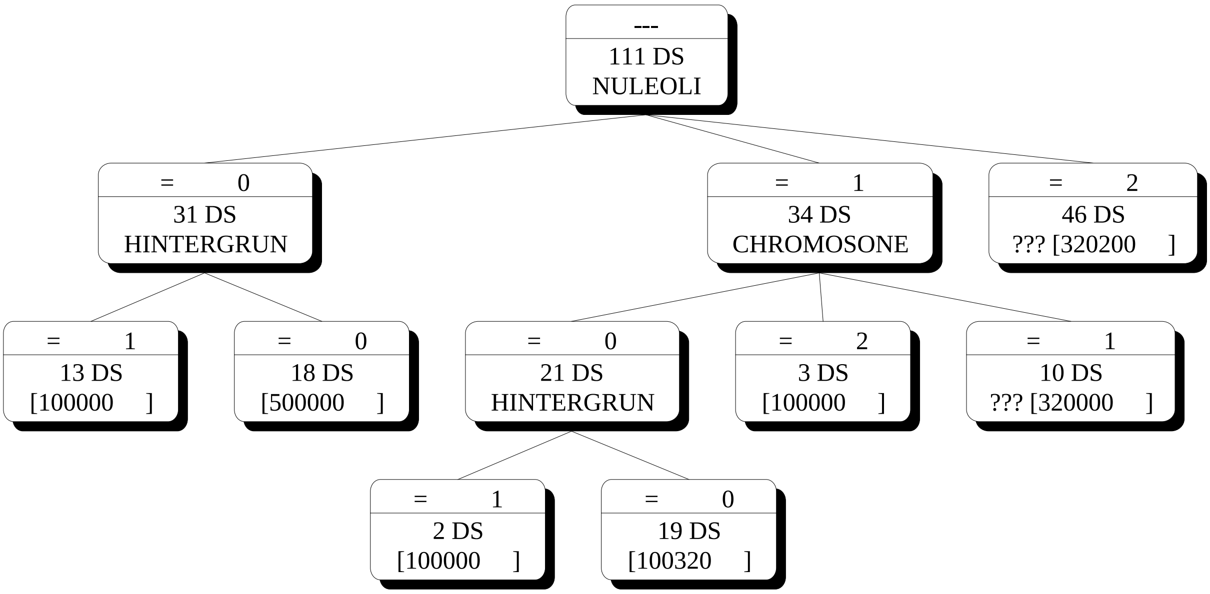


Figure 8 Decision Tree obtained from Expert´s Readings

P. Perner, Image Mining: Issues, framework, a generic tool and its application to medical-image diagnosis, Journal Engineering Applications of Artificial Intelligence,vol. 15/3, pp. 193-203

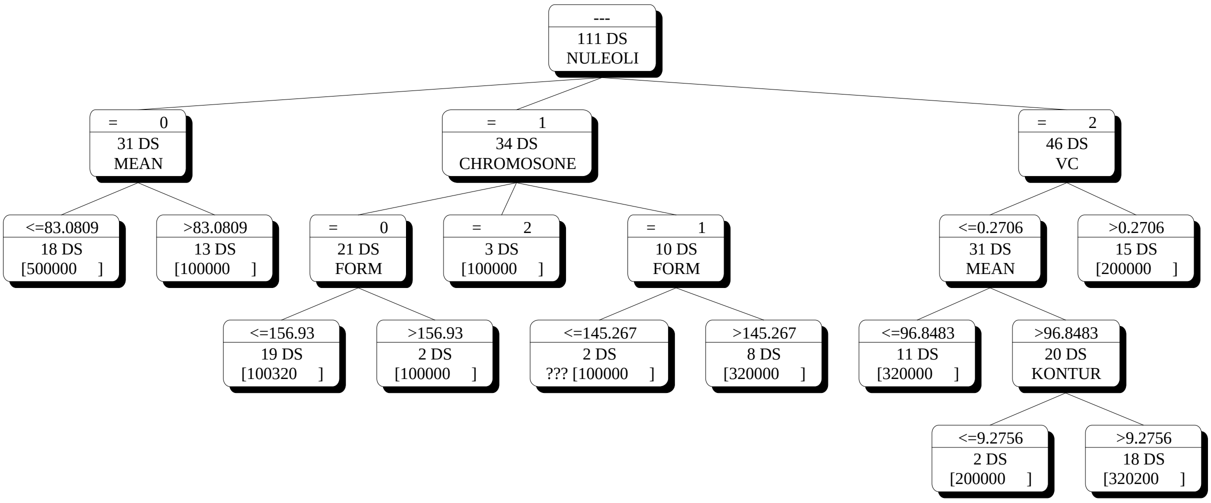


Figure 9 Decision Tree obtained from Expert´s Readings and Image Readings

Attribute	**Code**	**Attribute Values**
Interphase Cells	0	Undefined
	1	Fine speckled
	2	homogeneous
	3	Coarse Speckled
	4	Dense fine speckled Fluorescence
Nucleoli	0	Undefined
	1	Dark area
	2	fluoresce
Background	0	Undefined
	1	Dark
	2	Fluorescence
Chromosomes	0	Undefined
	1	Fluorescence
	2	Dark
Cytoplasm	0	Undefined
	1	Speckled Fluorescence
Classes	100 000	Homogeneous
	100 320	Homogeneous fine speckled
	200 000	Nuclear
	320 000 320 200	Fine speckled Fine speckled nuclear

Table 1 Attribute List

	Error Rate		
Data Set	Expert	Unpruned Tree	Pruned Tree
Original Data Set	5 %		
Expert Readings		27 %	27 %
Automatic Feature Analysis		27 %	27 %
Combined Data Set		6,9 %	6,9 %

Table 2 Error Rate for Decision Trees obtained from the different data bases