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On Automation of Brain CT Image Analysis

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***Abstract*—During recent years a number of medical diagnosis support systems have been presented. Such systems are important from medical point of view, because they aid physicians in their daily work. Some of those systems, like *Computed tomography* support systems (CT) rely on image data analysis, making it an interesting research topic from pattern recognition point of view. The paper presents a practical realization of a medical support system, including segmentation, feature extraction and decision processes. Various techniques are used within the system: fuzzy logic, shape descriptors, classifiers and automatic image annotation framework. Series of 2D CT images are an input of the system. As a result, a patient's diagnosis is presented.**

I. Introduction

IN THE paper we present an approach to introduce automation of brain CT image analysis. Our goal is to support physicians (radiologists) in their daily work. In the first step of authors' research, the system has to classify a set of 2D CT images with respect to the presence or absence of brain atrophy. To be able to support radiologists, the constructed system has to generate diagnoses which are as similar as possible to expert's ones. To comfortably support radiologists, the system has to work within limited, reasonable time constrains. Analysis of brain CT images can be helpful in diagnosis of many diseases, including dementive diseases. Diagnosing process of dementive diseases is complicated. Although brain lesions appear 10–20 years prior to clinical manifestation, they are subtle and unavailable for standard diagnosing methods. Thus there are many researches during last few years trying to use neuroimaging procedures for diagnosing dementive diseases, such as Alzheimer's disease.

Several pattern recognition and machine vision techniques are used in the presented approach. A single 2C CT image is segmented using a fuzzy logic based algorithm.Afterward, feature vectors are calculated on the basis of extracted brain fluid segments. Classification of a patient's state is the final step. Several approaches to classification are examined. The first one is a classic multilayer perceptron (MLP). The second and the third ones are two automatic image annotation methods. Those methods are: *Binary Machine Learning* [6] using a set of *C4.5* decision trees and *Continuous Relevance Model* [4] using Gaussian kernel distance calculation. One of authors' goals during the research is to evaluate the usage of automatic image annotation framework for the stated classification problem.

The article is organized in the following manner. Next section states the problem from a medical point of view. The proposed approach is described in the third section. A brief description of all used algorithms and methods is presented. The fourth section presents performed experiments. The last section summarizes the article.

II. Problem statement

The most common dementia diagnosis method is visual evaluation of brain fluid spaces done by radiologist. It is quick and hardware-independent, however not perfect: it requires experienced specialist, and is descriptive and subjective [2]. More objective method is making planimetric measurements, but this is time-consuming, both during evaluation and generating results, which are relative to brain volume [5].

The most advanced method is automatic volumetric measurement of intracranial fluid. Programs used to evaluate cerebral fluid volume work on a semi-automatic basis—the specialist selects region of interest, and the specified volume is measured [7]. The next step is to make the diagnosis quicker by introduction of a fully automated method.

The automation of brain atrophy evaluation in patients with dementia on the basis of brain CT images analysis can be performed using different approaches. One is developing an effective and precise method of region of interest automatic segmentation.Afterward, region of interest volume can be measured. The second approach, proposed in this paper, is based on applied automatic annotation method which classifies brain CT images as *brain atrophy* or *no brain atrophy*. Such a method is evaluated by physicians as very helpful in dementia diagnosis process, because brain atrophy suggests dementive diseases. Taking into account above statements, the goal of this paper can be defined as follows: **To introduce a method of automatic patients discrimination with and without brain atrophy.**

The presented results are a part of wider research on CT image analysis, including image segmentation, feature generation and diagnosis support. Apart of the main goal, following research goals are defined:

- Determination if it is possible to build CT decision support system using features based on intracranial fluid area.
- Evaluation of the proposed architecture and all its components as a whole system.
- Evaluation of classification quality using features other than volume (area) of intracranial fluid.

- Evaluation of classification quality based on automatic image annotation framework in simplest 2 word case, for further research on larger dictionaries (more detailed patient's state description).

III. Proposed approach

The goal of the proposed method is to automatically discriminate between patients with brain atrophy, which might suggest dementive disease. To achieve this a series of CT images is gathered and processed. A series of 2D CT images are used as an input of the method. Images represent brain slices, gathered during the scanning process. Together, they form a 3D CT brain image. The system output is the patient's state diagnosis.

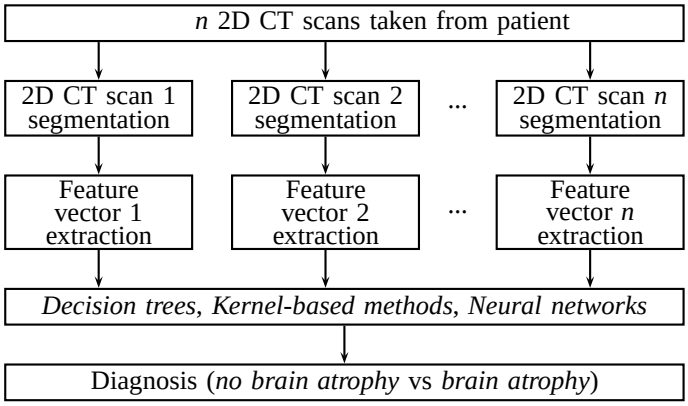


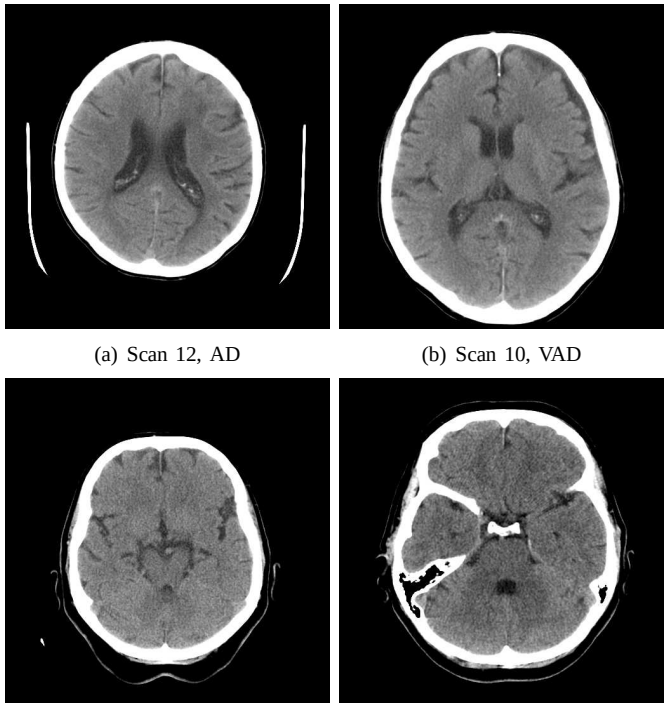
Fig. 1. Process of patients discrimination with and without brain atrophy

The proposed approach utilizes segmentation, feature vectors extraction and various classification techniques. Each of those steps is described in detail in this section. The whole process is visualized in Fig. 1. The goal of segmentation is to extract the *region of interest*, abbreviated *ROI*. Feature vectors are calculated on the basis of *ROI*. They are a set of synthesized, numerical values describing series of 2D CT scans. A set of classifiers is responsible for the final diagnosis.

A. Image acquisition

CT scans are acquired using two-slice helical General Electric (GE) CT/e Dual scanner. Patient's head is located between X-ray source and the rows of detectors. Detectors and the lamp are rotating by 360 degrees for each scan. Acquired raw data are transformed, using Fourier transformation to 2D images. Each scan is 7 mm thick and there's no gap between the slices, so put up together all scans show complete volume of the brain and intracranial fluid. Every single pixel of 2D picture is described by value known as density, measured in Hounsfield Units (HU) and may vary between -3000 (air), through 0 (water) to 3000 (bones, metals). Only a fraction of the density range is important from the diagnostic process point of view. Original images are rescaled to the important density range and then discretized to 8-bit grayscale. As a result of image acquisition series of 512x512 8-bit grayscale images are produces.

Exemplary CT scans for four different patients are shown in Fig. 2. The first image from the left shows the 12-th scan with diagnosed *Alzheimer disease* (abbreviated *AD*). The second image shows the 10-th scan with diagnosed *Vascular Dementia* (abbreviated *VAD*). The third and the fourth scans are taken for healthy patients.



(a) Scan 12, AD (b) Scan 10, VAD

(c) Scan 9, no disease (d) Scan 8, no disease

Fig. 2. Exemplary CT scans for various patients. Patient (a) has *Alzheimer disease*, (b) has *Vascular Dementia*. patients (c) and (d) have no disease.

Analyzed CT scan range is also an important topic and requires discussion. As mentioned before, for each patient a series of scans is performed. CT scans taken from the bottom of the head have the lowest indexes and from the top of the head—the highest indexes. However, scans with the same indexes do not relate between patients. Differences can be quite large, mostly because of the scanning process itself. Patient's head position is one of the most problematic factors. Additionally, scans from the bottom of the head contain many artifacts, due to bone presence and scanning process. It is worth to mention, that scans do not contribute to brain atrophy analysis, equally.

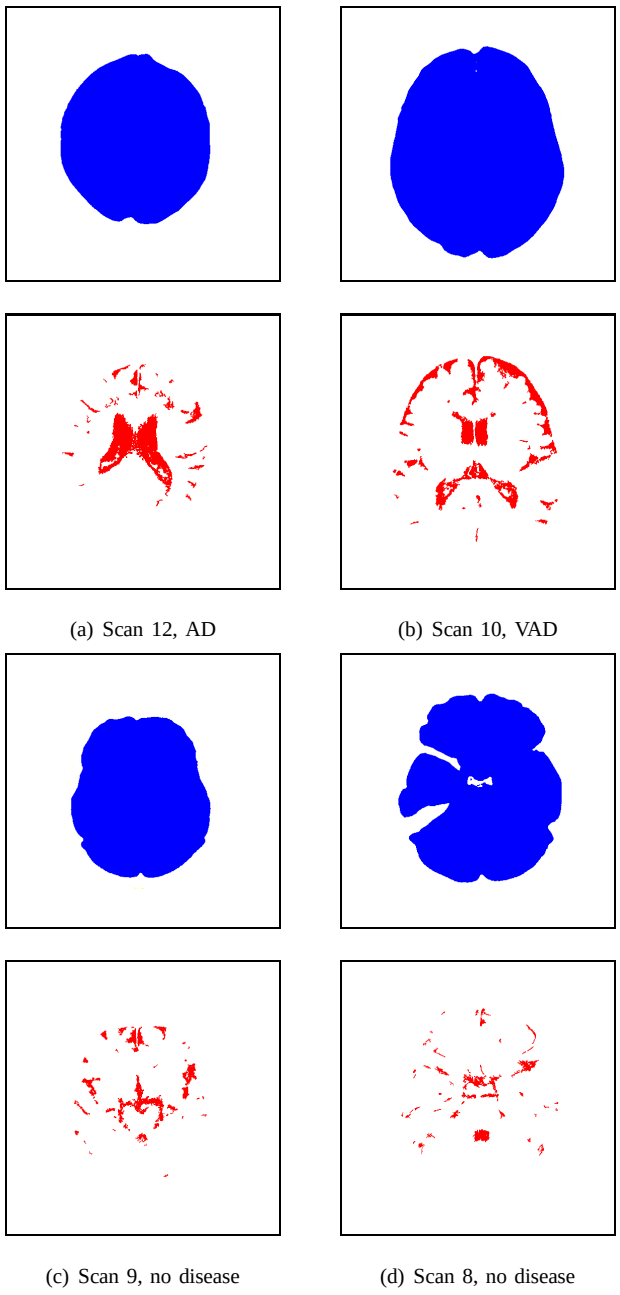
B. Image segmentation

Acquired 2D CT scans are processed by a specialized segmentation algorithm.The segmentation process extracts *cerebrospinal fluid area*. The method emulates the complexity of the standard radiological and neurological recognition, by definition of appropriate linguistic variables in accordance with a priori introduced fuzzy rule base. In the used method the Mamdani model [1] and the Larsen implication are considered. The COA (center of area) is applied as defuzzification method.

The key point of the proposed segmentation method (considered as a region growing segmentation technique) assumes homogeneity segmentation criteria that are defined upon a fuzzy control system, dedicated to computed tomography imaging. The growing process is controlled by a fuzzy control system and thus it classifies a pixel to a certain region (defined by a *seed*) if and only if the corresponding pixel characteristics are greater than or equal to some a priori given threshold value (denoted by T), considered as an output value of the fuzzy system. A formal treatment of the growing process is given below:

Let P be the set of all image pixels for a given image of size $M \times N$, $P =_{df} \{p(m,n)|m = 1,2,...,M; n = 1,2,...,N\}$ and let $P_s \subset P$ be the subset of all seeds generated for the considered image. Any neighbor pixel of a seed $p_k(x,y) \in P_s$, i.e. $p_k(x+i, y+j)$, where $i,j \in \{-1,0,1\}$ (excluding $i = j = 0$) belong to a region determined by the seed if and only if the output of the fuzzy system corresponding to this neighbor pixel is $\geq T$. In our experiments the possible primary input states for the fuzzy system (the characteristics considered for any pixel) are interpreted as the pixel colour and its localization on the image. This is because the radiological knowledge of the issue (the dementia problem) assumes that pixel represents cerebrospinal fluid if it is *dark* and it is *close* to the cranium or it is *dark* and it is *close* to the central parts of the image.

Results of the segmentation process for exemplary CT scans are presented in Fig. 3. Brain tissue is marked with blue in upper images. Cerebrospinal fluid is marked with red in lower images. The same CT scans are used as in Fig. 2.



(a) Scan 12, AD (b) Scan 10, VAD

(c) Scan 9, no disease (d) Scan 8, no disease

Fig. 3. Segmentation of exemplary CT scans for various patients. Upper row, blue images show the brain tissue area. Lower row, red images show the cerebrospinal fluid area.

C. Feature vectors calculation

Feature vectors calculation is necessary for further decision process. They are one of the method's key components, because they represent the synthesized form of patient's CT image scans. A set of geometrical, real valued features is selected [3]. Feature values are calculated using extracted cerebrospinal fluid area and brain tissue area.

Two feature sets are considered. The first one, named *FS1*, contains information only about area (volume) of the cerebrospinal fluid. Absolute and relative area of the fluid is taken from each scan. This method resembles manual, volumetric approach to patient's examination (cerebrospinal fluid volume calculation). In this approach, cerebrospinal fluid areas are the basic data for the decision process.

The second one, named *FS2*, consists of many other, shape related features. Absolute and relative circumference and center of mass are taken into account. Additionally, a series of shape coefficients are used. All used features are presented in Tab. I.

Patient's examination results in a series of 2D CT scans. On the basis of acquired and segmented CT scans a set of feature vectors is calculated. Each feature value is calculated for the whole CT image using the segmentation output. The process results in a non-square matrix of values generated for one patient. The following symbols are used in the given definitions:

– i—number of pixel within object,
– L—circumference of cerebrospinal fluid,
– S—area of cerebrospinal fluid,
– L_B—circumference of brain tissue,
– S_B—area of brain tissue,
– r_i—distance of a pixel from the center of the mass,
– d_i—distance of a contour pixel from the center of the mass,
– l_i—minimum pixel distance to the object contour,

TABLE I
FEATURES CALCULATED FOR A SINGLE, SEGMENTED CT SCAN. *FS1* REPRESENTS THE FIRST USED FEATURE SET, *FS2* REPRESENTS THE SECOND ONE.

Feature	*Definition*	*FS1*	*FS2*
Number of scan	n	yes	yes
Absolute circumference	L	no	yes
Absolute area	S	yes	yes
Relative circumference	$L_{rel} = \frac{L}{L_B}$	no	yes
Relative area	$S_{rel} = \frac{S}{S_B}$	yes	yes
Malinowska Coefficient	$R_M = \frac{L}{2\sqrt{\pi S}} - 1$	no	yes
Modified Malinowska Coeff.	$R_{mM} = \frac{2\sqrt{\pi S}}{L}$	no	yes
Blair-Bliss Coefficient	$R_B = \frac{S}{\sqrt{2\pi(\sum_i r_i)^2}}$	no	yes
Blair-Danielsson Coeff.	$R_D = \frac{S^3}{\left(\sum_i l_i\right)^2}$	no	yes
Haralick Coefficient	$R_H = \sqrt{\frac{(\sum_i d_i)^2}{n\sum_i d_i^2 - 1}}$	no	yes
Feret Coefficient	$R_F = \frac{L_h}{L_v}$	no	yes
Circularity Coefficient 1	$R_{C1} = 2\sqrt{\frac{S}{\pi}}$	no	yes
Circularity Coefficient 2	$R_{C2} = \frac{L}{\pi}$	no	yes
Center of mass in X	$R_{mx} = \frac{\sum_i x_i}{\sum_i 1}$	no	yes
Center of mass in Y	$R_{my} = \frac{\sum_i y_i}{\sum_i 1}$	no	yes

– L_h—maximum width of the object,
– L_v—maximum height of the object.

L and L_B values are calculated using the following approach. Each pixel in the image, excluding image boundary pixels, is analyzed if it is a ROI boundary pixel. Only ROI boundary pixels are considered in the circumference value calculation. The process is a lookup procedure using a 3×3 pixels mask. A pixel is ROI boundary if and only if the center pixel is lit and at least two pixels in the masked area are not lit. In case not lit masked pixels are placed on the diagonal, the pixel contributes $\sqrt{2}$ to the circumference value, in all other cases it contributes 1.

Normalized feature vectors are required by classification methods. All presented features are normalized using linear transformation to $\langle 0; 1\rangle$ interval. Each feature's lower and upper normalization bound is selected as the lowest and highest value from the available data.

D. Decision making

The last step performed by the proposed medical support system is decision making. Three approaches are presented and evaluated. The first one is a classic multilayer perceptron neural network. The second and the third methods are based on automatic image annotation framework. All used methods are supervised machine learning and require a training set. Training examples are a set of manually diagnosed CT images. Manual diagnoses are performed by the radiologist and thus they represent medical domain knowledge.

1) Classification using multilayer perceptron: The first approach to decision making is a classic multilayer perceptron. In the presented approach, 3-layer perceptron is used. Number of neurons in the input layer is equal to the number of features in a single feature vector. Number of neurons in the output layer is equal to the number of output classes. Size of the hidden layer is calculated using a standard rule and is equal to the average size of input and output layer. Number of training epochs is equal to 500, learning rate is equal to 0.3 and momentum coefficient to 0.2.

Final decision process is the following. Each feature vector is classified using the neural network. Results are aggregated and the dominant class in all classification runs is selected.

2) Classification using automatic image annotation approach: In general, an automatic image annotation method describes an input image (represented as a set of feature vectors) with a subset of words from the given *dictionary*. Input of image annotation is a set of feature vectors and a dictionary. Output of automatic image annotation is a subset of dictionary. The goal of the method is to select the subset in best possible way, according to presented *training examples*. In this case, the dictionary is reduced to only two possible choices: *brain atrophy* and *no brain atrophy* (*brain atrophy* is treated as a single word, similarly as no brain atrophy). Output of the method is also reduced to only one word, being the diagnosis. Our goal is to verify if automatic image annotation framework can be used for the stated classification problem. Successful verification will lead to further research, with larger dictionaries.

Two automatic image annotation methods are examined for the stated problem. The first one is *Continuous Relevance Model* [4], abbreviated *CRM*. It is based on distance calculation between processed feature vector and feature vectors from the training set. This method uses distance measure based on *Gaussian kernel*. Words are propagated from the training set into the processed feature vectors with respect to the measured distance. The farther the feature vectors are, the lesser the influence is.

The second method is *Binary Machine Learning* [6], abbreviated *BML*. It employs a series of decision trees, constructed using *C4.5* algorithm. Each decision tree relates to one class from the dictionary and is responsible for generation of positive or negative answers. A positive answer given by a decision tree contributes to the word the tree represents. If the tree gives a negative answer, no word contribution is made. In case of n words (in this case $n = 2$), n decision trees is required.

IV. EXPERIMENTS

The goal of conducted experiments is to show the method's ability to automatically discriminate between *brain atrophy* and *no brain atrophy* CT images. Experiments are performed on a set of CT images acquired from patients with various types of brain disorder and with no disorder. Segmentation and feature calculation are performed according to the presented routines. Three methods of patients discrimination are tested: *Multilayer perceptron neural network*, *Continuous Relevance Model* and *Binary Machine Learning*.

A. Medical data and quality evaluation

Available medical data are divided into four categories according to the disease type (Tab. II). In each category a number of patients are examined. There are total 72 examinations available. Patients with three disease types are included in the performed experiments: *Alzheimer disease*, *Mixed Dementia* and *Vascular Dementia*. Patients with no brain atrophy are the fourth group. Examined patients are in different age and have different education level.

TABLE II
NUMBER OF PATIENTS ACCORDING TO THE DISEASE TYPE. CLASSIFICATION USED IN THE AUTOMATED PROCESS IS PRESENTED IN THE THIRD COLUMN.

Disease type	*Number of patients*	*Class*
No disease	20	no brain atrophy
Alzheimer disease	35	brain atrophy
Mixed Dementia	12	brain atrophy
Vascular Dementia	5	brain atrophy

Results quality evaluation is done with respect to manually prepared diagnoses. Those diagnoses are the reference point both in training and testing processes. All experiments are performed using *leave-one-out* validation procedure. The following values are calculated to evaluate quality: true positives, false positives, true negatives, false negatives, false positives ratio, false negatives ratio and overall accuracy.

To make this discussion more complete, we also address the accuracy baseline. Baseline value for accuracy is equal to 72% and it is calculated for a naive approach. To maximize accuracy, every case is classified to the most common class, without any feature consideration. For the presented data, the most common class is *brain atrophy*. This means that there are only positive answers (true positives and false positives) and no negative answers.

B. Results

Manual diagnosis is performed by medical doctors, radiologists specialized in CT image analysis. This approach is the reference one. It requires a lot of manual labor, thus is expensive and prone to potential errors. Automated diagnosis is performed using the proposed method. Detailed information on classification results are presented in Tab. III. True positives, true negatives, false positives and false negatives are listed. Selection of feature set (*FS1* or *FS2*) has the largest influence on the achieved results. Selection of scan range and classification method have smaller influence. According to the performed experiments, usage of *FS2* results in much higher quality of results than usage of *FS1*. *BML+FS1* gives a large number of type II errors (false negatives). *CRM+FS1* gives a large number of type I errors (false positives). In one case, true negatives and false negatives have not been generated at all, which means that the method have not generated any negative answer. *MLP+FS1* approach fails on generation of negative answers and proves to be unusable.

As mentioned before, usage of *FS2* results in much better results. Number of true positives for both combinations (*CRM+FS2* and *BML+FS2*) is comparable or larger than for *CRM+FS1*, and number of true negatives is comparable to *BML+FS1*.

TABLE III
BRAIN ATROPHY VERSUS NO BRAIN ATROPHY DETAILED CLASSIFICATION RESULTS FOR EXAMINED APPROACHES. TP STANDS FOR TRUE POSITIVES, TN—TRUE NEGATIVES, FP—FALSE POSITIVES, FN—FALSE NEGATIVES.

Used approach	*TP (correct)*	*FP (type I error)*	*TN (correct)*	*FN (type II error)*
Scan range: All				
CRM+FS1	30	10	10	22
BML+FS1	35	2	18	17
MLP+FS1	51	16	4	1
CRM+FS2	49	4	16	3
BML+FS2	51	6	14	1
MLP+FS2	48	3	17	4
Scan range: 5-15				
CRM+FS1	52	20	0	0
BML+FS1	33	2	18	19
MLP+FS1	52	20	0	0
CRM+FS2	50	5	15	2
BML+FS2	52	13	7	0
MLP+FS2	49	7	13	3
Scan range: 10-15				
CRM+FS1	42	13	7	10
BML+FS1	32	4	16	20
MLP+FS1	52	20	0	0
CRM+FS2	46	5	15	6
BML+FS2	50	6	14	2
MLP+FS2	49	8	12	3
Scan range: 12-15				
CRM+FS1	50	20	0	2
BML+FS1	35	4	16	20
MLP+FS1	52	20	0	0
CRM+FS2	47	2	18	5
BML+FS2	49	7	13	4
MLP+FS2	50	4	16	2

Achieved accuracies and negative rates are presented in Tab. IV. Averaged results are the confirmation of the discussion, presented above. Usage of *FS2* in general leads to better results, comparing to *FS1*. In terms of accuracy, selection of the annotation method do not have large influence on the quality. Presented results suggest that *MLP+FS2* with scan range *12-15* should be selected as the best approach. Usage of *MLP+FS2* with scan range *12-15* results in accuracy equal to 92%. *CRM+FS2* approach also provided good results. Accuracy is equal to 90% (only 1 more patient is incorrectly classified, compared to *MLP+FS2*), false positives and false neatives rates are both equal to 10%.

C. Discussion

Achieved results are satisfying and can be viewed as a good basis for further research. When provided with a proper feature set, all three approaches to classification give similar results. There is a large difference in results quality between tested feature sets. The first one, which is based only on cerebrospinal fluid areas, provides unsatisfactory results. However, when the feature vector is extended, quality is increased. Examined scan ranges do not influence the results quality in a large manner. Best results are achieved for scan range 12-15, however usage of all scans gives only very minor decrease in quality (1 more patient is misclassified).

TABLE IV
BRAIN ATROPHY VERSUS NO BRAIN ATROPHY AVERAGED CLASSIFICATION RESULTS FOR EXAMINED APPROACHES.

Used approach	*FP rate*	*FN rate*	*Accuracy*	*Relation to baseline*
Scan range: All				
CRM+FS1	0.50	0.42	0.56	below baseline
BML+FS1	0.10	0.33	0.74	above baseline
MLP+FS1	0.80	0.02	0.76	above baseline
CRM+FS2	0.20	0.06	0.90	above baseline
BML+FS2	0.30	0.02	0.90	above baseline
MLP+FS2	0.15	0.08	0.90	above baseline
Scan range: 5-15				
CRM+FS1	1.00	0.00	0.72	baseline case
BML+FS1	0.10	0.37	0.71	below baseline
MLP+FS1	1.00	0.00	0.72	baseline case
CRM+FS2	0.25	0.04	0.90	above baseline
BML+FS2	0.65	0.00	0.82	above baseline
MLP+FS2	0.35	0.06	0.86	above baseline
Scan range: 10-15				
CRM+FS1	0.65	0.19	0.68	below baseline
BML+FS1	0.20	0.38	0.67	below baseline
MLP+FS1	1.00	0.00	0.72	baseline case
CRM+FS2	0.25	0.11	0.85	above baseline
BML+FS2	0.30	0.04	0.89	above baseline
MLP+FS2	0.40	0.05	0.85	above baseline
Scan range: 12-15				
CRM+FS1	1.00	0.04	0.69	below baseline
BML+FS1	0.10	0.33	0.74	above baseline
MLP+FS1	1.00	0.00	0.72	baseline case
CRM+FS2	0.10	0.10	0.90	above baseline
BML+FS2	0.35	0.06	0.86	above baseline
MLP+FS2	0.20	0.04	0.92	above baseline

Let us relate to the stated research goals, now. Construction of a CT decision support system is possible, however great care has to be made during feature selection process. Areal features seem to be insufficient and other shape related features must be introduced. The presented support system architecture gives satisfactory results. Having the accuracy baseline value equal to 72%, authors have achieved maximum classification accuracy reaching 92%. Verification of automatic image annotation framework is also positive. Achieved results are similar to those with standard classification approach.

V. SUMMARY

A method for automatic discrimination of brain-atrophic patients with possible dementive disease and patients with no brain atrophy is proposed. A series of 2D CT scans, representing the 3D brain image is given as input. Each scan is segmented by a specialized routine, extracting the cerebrospinal fluid and nervous tissue. A set of feature vectors is calculated on the basis of segmentation and they are input of a classification method. Afterward, feature vectors are processed and a diagnosis is generated.

Achieved results are very promising. For the best presented combination of feature set, scan range and classification method, accuracy reaches 92%. It means that the automatic method is able to repeat expert's manual diagnoses in most cases. Additionally, the automated process is not time consuming and can be used as a live aid in medical doctors daily work.

The proposed method could be also used for prospective and populational researches due to its speed and repeatability of output scores. Another possible usage is the evaluation of possible changes in atrophy degree, e.g. during treatment—especially in experimental methods of treatment. Further research will be focused on introduction of new, shape related features characterizing the cerebrospinal fluid. Additionally, a larger dictionary (with more detailed diagnoses) will be proposed for the image annotation approach.

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