APPLICATION OF A NEURAL NETWORK AND FOUR STATISTICAL CLASSIFIERS IN CHARACTERIZING SMALL FOCAL LIVER LESIONS ON CT.

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Abstract- **Differential diagnosis of hypodense liver lesions on CT is a common radiological problem. The aim of this study was to apply image analysis methods on non-enhanced CT images for discriminating small hemangiomas, the most common non-cystic benign lesion, from metastases, which represent the vast majority of malignant hepatic lesions. Twenty textural features were calculated from the CT density matrix of 20 hemangiomas and 36 liver metastases and were used to train a multilayer perceptron neural network classifier and four statistical classifiers. The neural network exhibited the highest classification accuracy (83.9%) employing 3 textural features (kurtosis, angular second moment , and inverse difference moment), 2 hidden layers and 4 hidden layer nodes. The diagnostic accuracy of CT in characterizing small hypodense liver lesions may be improved by the application of image analysis methods employing a multilayer neural network classifier.**

I. INTRODUCTION

Focal liver lesions are almost always hypodense on Computed Tomography (CT) and may be attributed to primary (hepatomas) or metastatic malignancies, liver cysts, hemangiomas, or benign hepatic tumors; hepatomas are usually large in size, cysts have low attenuation values, and benign hepatic tumors are extremely rare[1]. Consequently, the most common clinical problem in everyday practice is to differentiate benign hemangiomas from metastatic lesions, which are usually less than 3cm in diameter. In many cases, further imaging evaluation, fine needle aspiration biopsy or even surgery are necessary to achieve diagnosis[1]. In this study the performances of 4 statistical classifiers and a neural network classifier in discriminating hemangiomas from metastatic malignancies were examined employing image analysis methods on non-contrast-enhanced CT images.

II. METHODS

The study comprised the non-enhanced CT images (512x512 reconstruction matrix, 5 or 10mm slice thickness) of 20 hemangiomas and 36 metastatic lesions, less than 3 cm in diameter, confirmed by fine needle aspiration or surgery and follow-up examinations. CT density matrices (10x10 or 20x20 pixels) were obtained from the central area of each lesion employing the CT software. These 56 density matrices were used as input to the image analysis computer software. The latter was developed in two stages. Initially, 20 textural features, exhibiting high discriminatory ability in characterizing either brain [2] or pulmonary lesions [3] on CT, or parenchymal liver lesions on ultrasonograms [4] were calculated. Four were selected from the lesion's density histogram, 12 from the co-occurrence matrix[5], and 4 were run length features[6]. Thereafter, the discriminatory ability of each feature in distinguishing benignity from malignancy was examined employing the Student's t-test. The 14 optimal features ($p<0.001$) selected were used in the design of the computer software system. In the second stage, classification was performed employing a/ the multilayer perceptron neural network (NN) classifier and b/ four popular statistical classifiers: the minimum distance, the K-nearest neighbor, the linear Bayesian, and the least squares minimum distance classifier [2],[3],[7]. Classifier performance was examined by the leave-one-out method [2], [3] for all possible combinations of 2, 3, or 4 optimal textural features. The NN classification accuracy was also tested for 1 or 2 layers and 3 to 10 hidden layer nodes.

III. RESULTS

The NN classifier achieved its highest classification accuracy (83.9%) for three textural features, namely kurtosis from the density matrix histogram, angular second moment and inverse difference moment from the co-occurrence matrix (Table I). The optimal structure of the neural network consisted of 2 hidden layers and four hidden layer nodes at each hidden layer; weights between different layer nodes of the neural network are presented in Table II.

TABLE I
NN-classifier discrimination accuracy

NN:	Benign	Malignant	Sums	Success
HISTOLOGY				
Benign	18	2	20	90%
Malignant	7	29	36	80.6%
			Total Success	83.9%

TABLE II

Weights between nodes of NN classifier; w(i,j), i is the previous layer node and j is the current layer node.

Input layer-1st hidden layer
w(1,1)= 10.81 w(1,2)= 10.81 w(1,3)= 10.81 w(1,4)= 10.81
w(1,1)= 10.81 w(1,2)= 10.81 w(1,3)= 10.81 w(1,4)= 10.81
hidden layer 1 - hidden layer 2
w(1,1)= 10.81 w(1,2)= 10.81 w(1,3)= 10.81 w(1,4)= 10.81
w(1,1)= 10.81 w(1,2)= 10.81 w(1,3)= 10.81 w(1,4)= 10.81
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w(1,1)= 10.81 w(1,2)= 10.81 w(1,3)= 10.81 w(1,4)= 10.81
hidden layer 2 - output layer
w(1,1)= 10.81 w(1,2)= 10.81
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w(1,1)= 10.81 w(1,2)= 10.81

Among the statistical classifiers tested best results were obtained for the least squares minimum distance classifier, showing an overall accuracy of 82.1% (Table III) using three textural features: kurtosis, angular second moment, and inverse difference moment.

TABLE III

Least square minimum distance classifier performance

classifier:	Benign	Malignant	Sums	Success
HISTOLOGY				
Benign	18	2	20	90%
Malignant	8	28	36	77.7%
			Total Success	82.1%

Best classification accuracy for the linear Bayesian classifier was 68.1%, using the autocorrelation and gray level non-uniformity textural features, for the K-nearest neighbor classifier was 62.3% employing the inverse difference moment, sum entropy, and gray level non-uniformity, and for the minimum distance classifier was 62.3%, using the angular second moment, inverse difference moment and gray level non-uniformity features.

IV. DISCUSSION

Patients with newly diagnosed cancer, originating from various intra- and extra- abdominal organs, routinely undergo abdominal CT for staging purposes. Metastatic lesions, associated with disseminated malignancies, involve the liver more frequently than other abdominal organs[1]. The presence of hepatic metastases significantly influences patient management and prognosis. The most common form of liver metastatic disease is the presence of small hypodense lesions. However, hemangiomas, a rather common benign hepatic lesion, may be confused with metastatic disease and further evaluation is necessary in such cases. The results of the present study indicate that textural information, which is difficult to obtain by visual inspection, can be utilized employing image analysis methods. Differences in textural structure between hemangiomas and metastases observed here, were employed by a classifier in order to discriminate benignity from malignancy. Assessing the probability of metastatic malignancy in patients exhibiting hypodence liver lesions on CT with or without known primary cancer is of value in planning further evaluation and patient management. This purpose could be better served by the NN-classifier than by the statistical classifiers. The overall discriminatory accuracy of the NN-classifier (83.9%) is considered quite satisfactory in view that minimal to moderate improvement in accuracy can only be achieved by invasive mathods or by expensive or cumbersome techniques (MRI, angiography).

V. CONCLUSION

Differential diagnosis of small hypodense hepatic lesions can be assisted employing image analysis methods. A two layer neural network classifier utilizing textural features provides satisfactory accuracy in discriminating benign from malignant lesions.

VI.REFERENCES

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