NEURAL NETWORK APPLICATION IN ECO-ULTRASOUND BRIGHTNESS PREDICTION ASSOCIATED WITH HEPATIC DIAGNOSIS

Alina PLEŞEA-CONDRATOVICI[1], Cătălin PLEŞEA-CONDRATOVICI[1], Corneliu NEAMȚU[1], Mihaela BANU[2], Mitică AFTENI[2]

[1]Dentistry College University of Medicine and Pharmacy "Gr. T. Popa" Iaşi
[2]Faculty of Mechanical Engineering, Dunărea de Jos University of Galați

ABSTRACT

The imaging diagnostic is a useful tool which avoids further investigations. Usually, a lot of results are concurrent to diagnosis and a numerical tool with artificial intelligence could better use all these data to predict the stage of steatosis at the liver level. Our goal is to test a unified framework based on neural network application for image analysis in medical science. A number of 100 pacients are used for generating the data matrix in order to build a NEUROSTEATOSIS trained neural network. Ten variables are decided, seven are for input parameters and three for output parameters. The neural model establishes a correlation between the input and output parameters in order to predict interrogated values between the range of trained ones. The results were validated with some results based on another investigations applied to other pacients for whom the level of steatosis is known. This new tool could be further used for a preliminary estimation of the progress of steatosis in certain conditions.

KEYWORDS: neural network, ultrasonography, numerical analysis, brightness, hepatic steatosis

1. INTRODUCTION

The improvement of image diagnostic machines and the increasing availability of extensive medical data have triggered the development of new analytical methodologies in the context of medical informatics. The goal is to extract useful information and support clinicians in their accuracy demanding decision making tasks. From simple summarizing statistics to complex pattern analysis algorithms and neural networks applications , the underlying principles that drive most medical progress show trends that can be identified and taken into account to improve the usefulness of computerized medicine to the field of clinicians and finally to the patient [1].

Diagnosing imagining in biomedicine is based on several techniques and processes aiming at the enhancements of expert capabilities to evaluate imaging data. Diagnostic imaging combines image processing and decision support methods to improve and accelerate case-specific advice in clinical environments.

Decision support today focuses on diagnosis, prognosis, therapy and follow-up recommendations and is usually based on simple and easily acquired met in biomedical data. The latest break-troughs in imaging technologies lead to an explosion of imaging data available. New techniques and methods addressing mainly acquisition and processing of information from medical and biological images appeared and the integration of biomedical image data into decision support systems is a challenging task. This mainly supports the decision on the patient's health status and the quality of the extracted diagnosis and prognosis.

Despite the wide application of decision support systems in medicine, only a few systems have been developed for biomedical Although, there are many similar methods, each imaging modality and each type of pathology requires the development of dedicated low-level feature extraction. Although standard computer imagine analyzing techniques may be used, specific methodologies and algorithmic approaches need to be developed [2].

Ultrasound B-scan imaging has become one of the most popular modality to image human abdominal organs such as liver [3]. These images appear as textural ones and various techniques have been applied in order to characterize different tissues to normal or abnormal. Ultrasound imaging is a powerful tool for characterizing the state of soft tissues; however, in some cases, where only subtle differences in images are seen as in early stages of diffuse liver diseases such as steatosis or fibrosis and even in focal liver lesions such as hemangioma and malignancy, existing B-scan methods are inadequate [4]. Promising results in the area of Computer-aided diagnosis systems may offer new possibilities in the diagnosis and staging of tumor pathology [5,6]. More detailed analyses of ultrasonography image texture parameters along with artificial neural networks can be utilized to enhance differentiation from benign and malign tumors. The basic concept that stays at the base of computer aided ultrasonography diagnose is that structural modifications of the properties of human tissue generates modifications in ultrasonic image results.

Basically, all ultrasound imaging is performed by emitting a beam of ultrasound pulse, which is partly reflected from a boundary between two tissue structures, and partially transmitted. The reflection depends on the difference in impedance of the two tissues. Basic imaging by ultrasound does only use the amplitude information in the reflected signal. One pulse is emitted, the reflected signal, however, is sampled more or less continuously (actually multiple times). As the velocity of sound in tissue is fairly constant, the time between the emission of a pulse and the reception of a reflected signal is dependent on the distance; i.e. the depth of the reflecting structure. The reflected pulses are thus sampled at multiple time intervals (multiple range gating), corresponding to multiple depths, and displayed in the image as depth. Medical diagnostic ultrasound usually operates in the range 2-10 MHz for transcutaneous measurements, but frequencies up to 40 MHz have been used intraoperative and with intra-arterial imaging with ultrasound catheters. Transducer frequency Depth of penetration Higher frequencies attenuate, or are absorbed, faster than lower frequencies Time Gain Compensation Based upon the pulse-echo principle occurring with ultrasound piezoelectric crystals, ultrasound transducers convert: electricity into sound it is equal to producing ultrasound pulse and converts sound into electricity. Pulse of sound is sent to soft tissues, echo produced by soft tissue interaction with sound acoustic propagation properties. Echoes are received by the transducer and result results converted in electricity and then used to display an image. In mode B ultrasound Spatial Resolution describes how physically close two objects can be and displayed separately (i) *Axial* along the beam path and (ii) *Lateral* perpendicular to beam path. All current equipment has an overall spatial resolution of 1.0 mm or less.

2. Methods

The study group (N=100) was randomly selected from patients of a GP practice group. Subjects ages ranged between 32 and 75 years with a mean age of 61 ± 10.63 years (age ± SD - standard deviation)., the ratio men: women was 1.5: 1.The exclusion criteria were evidence of cirrhosis or other forms of chronic liver disease, including viral infection. Alcohol consumption was ascertained by the self-administered “alcohol use disorders identification test” (AUDIT). Use of drugs historically associated with causing NAFLD such as systemic glucocorticoids, tetracyclines, anabolic steroids or other known hepatotoxins was also assessed during screening and their use constituted an excluded case. Subjects were measured for blood pressure, height, weight and waist circumferences. Mean arterial blood pressure (MBP), body mass index (BMI) and waist hip ratio (WHR) were also calculated through standard equation. Blood samples (serum) were collected to determine some biochemical parameters: total glycerides (TG), total cholesterol (TC), and alanine aminotransferase (ALT) fasting plasma glucose (FPG). All subjects underwent ultrasonic examinations using a Fukuda UF-4100 ultrasound machine with a convex probe at 3.5 Mhz. Digital images thus obtained were extensively analyzed using Image J software (Wayne Rasband, National Institutes of Health, Bethesda) and numeric data were exported to Excel (Microsoft Corporation, Redmond, Washington, USA) The selected abdominal ultrasound images were then processed in order to extract a particular region of interest (ROIs). These ROIs have been automatically assigned using a predefined mask and manually adjusted in case of misalignment by a qualified physician so as to contain only right kidney and liver parenchyma from two areas, one proximal and the other distal to the transducer with no major blood vessels information or focal masses. Three ROIs were selected from each image and were consisted by circular areas no smaller than 1296 pixels, depending on the liver image particularities

Patients were scanned under fasting conditions.

Table 1 – Mean and standard deviation of the studied paramethers

	Age	Waist	BMI	WC	SBP	DBP	FPG	TC	TG
Mean	58.70	73.94	26.88	88.18	135.88	81.22	94.21	205.39	140.99
Stdv	10.63	12.03	4.12	13.41	18.88	16.45	33.53	44.08	83.95

Stdv= standard deviation, BMI= body-mass index (kg/m^2),WC = waist circumference, SBP= sistolic blood Presure, DBP = diastolic blood presure, FPG = fassting plasma glucose, TC = total cholesterol, TG = serum trygliceryes

In the supine and left lateral decubitus position, utilizing subcostal and statistical mean and standard deviation values of the determined parameters (Table 1) shows a relative homogeneous study group, with mean values of the laboratory and anthropometric data under the cut-off points for abnormality.
Stage I Hypertension was found on 37% subjects, 8% having stage II hypertension, 6% stage III and 49 % e normal blood pressure determination. Abnormal modification in serum cholesterol and triglycerides were observed in 68 % respectively 63% intercostal approaches. The time-gain compensation was set up to a fixed position.

3. Neural network prediction

Neural networks (NN) are a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. The role of neural networks is to create a dynamic model trained with a certain number of real cases and later to be used for interrogation on a different case but within the range of the trained parameters.
For this study, a NEUROSTEATOSIS neural network was built using the data obtained for 100 pacients having different levels of steatosis. For these pacients a group of medical investigations were performed which become variables for the NEUROSTEATOSIS tool.

3.1. Creating the neural network

The present neural network has seven input parameters: V1- Weight (kg), V2- Glycemia (mg/dl), V3-Total cholesterol, V4- HDL Cholesterol, V5-Trygliceridis, V6- Creatitninins, V7- TGP.
These variables were prelevated for 100 subjects. The output parameters are set up by picking up the level of fatty tissue in three different area of the liver undergone to ultrasound investigations. Thus, three output parameters are decided V8, V9, V10 representing the level of fatty tissue in the areas presented in fig. 1.

Ultrasounds analyses were performed for 100 pacients resulting in 100 input values for the present study. To overal characterisation of the fatty level of the analysed livers, some representative points of interest were selected and the brightness of the image was measured. The representative points of interest (ROI) are spots with a certain area and a new technique using AutoCAD was meant in order to pick up ROI in the same position for all 100 cases. Thus, in each ROI (1, 2 and 3 as presented in figure 3), the minimum, maximum, mean square of the gray brightness were measured. As discussed in setting up the neural method paragraph, these values are considered output values for NEUROSTEATOSIS neural model. V8 is the mean value of ROI no. 1, V9 is the mean value of ROI no. 2 and V10 is is the mean value of ROI no. 3. Each of V8 to V10 represents in fact the absolute level of the fatty in the considered area which in a real biopsy will give the stage of steatosis.

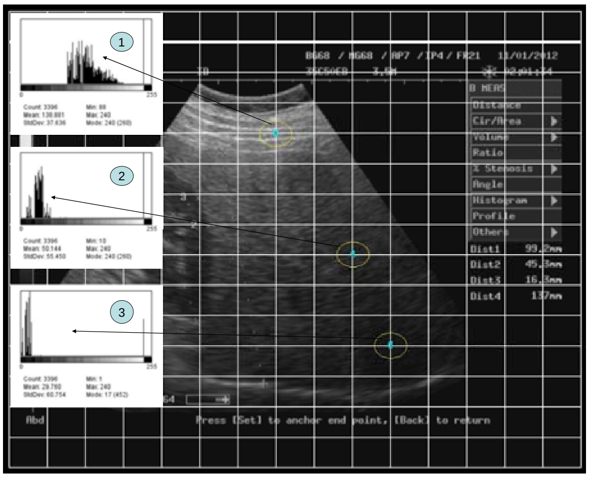

Figure 1 – The ultrasound investigation with the areas where the level of fatty tissues were measured (variables V8-V10).

The data represented in the associated histograms are picked-up aided by ImageJ software. The brightness for each gray in the figure obtained through out ultrasonography has a possible range between 0 (black) and 255 (white). Gray scale in this range is associated to different brightnesses corresponding to different grays. These grays are the reflected value of the ultrasounds according to the specific permeability of the tissues with normal morphology and partial-fatty morphology. The spot area of the ROI used for the three measured points was 0.774mm^2.
One hidden level of neurons is used (fig. 2).

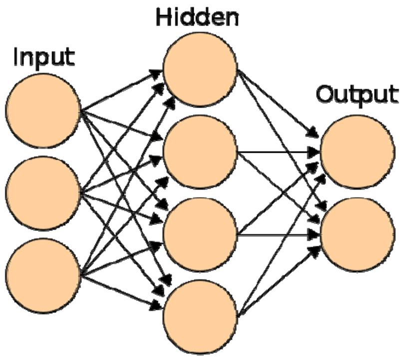

Figure 2 The model of the neural netowk

3.2. Training the neural network

The range for each parameter is decided by considering the minimum and the maximum value of each medical investigation. Thus, the range used are: V1 [54-92], V2[71-358.1], V3[89-366], V4 [35-141.1], V5[26-389], V6[0.6-1.4], V7[2-177.9], V8[54-100], V9[69-300], V10[43-578].

A number of 10000 steps were allowed for neural network to run in order to achieve an error of the prediction of 0.3%. The neural network determines a model based on correlation between the input parameters and the output parameters.

4. Results and discussions

The results are promising in developing a new useful tool for early detection of the possibility to develop hepatic steatosis. Even a pacient was not diagnozed with steatosis, by using a neural network which will be interrogated with the V1-V7 data of the pacient, the evolution of the steatosis could be predicted.

CONCLUSIONS

The use of neural network analyze in ultrasound brightness prediction associated with hepatic diagnosis is a promising tool. Further studies are needed. To build such a neural network are used 100 cases with a full set of data V1-V7 input parameters and V8-V10 output data. A prediction of the level of steatosis in different areas of the liver is predicted using the neural network with a prediction error of 0.3%.

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