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APPLICATION OF NEURAL NETWORKS IN THE CLASSIFICATION OF MEDICAL IMAGES TEXTURES

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ВИКОРИСТАННЯ НЕЙРОМЕРЕЖ ДЛЯ КЛАСИФІКАЦІЇ ТЕКСТУР МЕДИЧНИХ ЗОБРАЖЕНЬ

Neural networks have been widely used in medical diagnostic processes. Imaging results obtained from medical devices can be analyzed in many ways. One of them is to analyze the texture of the received images. Examination of the textures of diagnostic images is based on the determination of specific parameters and characteristics of examined tissue or organ. The main goal is to assign the analyzed area to one of two basic groups: as a healthy tissue or a tissue with pathological changes. By using supervised classification and setting up a training base, it is possible to achieve 93% accuracy in classification results.

Keywords: texture analysis, artificial neural networks, image classification, medical imaging

Нейронні мережі широко застосовуються в медичних діагностичних процесах. Результати обробки зображень, отримані з медичних приладів, можна аналізувати багатьма способами. Один з них - це аналіз текстури отриманих зображень. Вивчення текстур діагностичних зображень ґрунтується на визначенні конкретних параметрів та характеристик досліджуваної тканини або органу. Основна мета полягає в тому, щоб класифікувати аналізовану ділянку як одну з двох основних груп: як здорову тканину або тканину з патологічними змінами. Використовуючи контрольовану класифікацію та налаштовану навчальну базу, можна досягти точності результатів класифікації 93%.

Ключові слова: аналіз текстур, штучні нейромережі, класифікація зображень, медичні знімки

Inroduction

One of the most important sources of diagnostic information are images of internal organs. The key issue in the process of computer image processing is a clear and objective description of the areas that occur on them, called regions of interest (ROI). A valuable source of information on this subject is the image texture. The considered property may include, among others: image graininess, pattern direction, homogeneity, local contrast or average brightness level of pixels in each image area. They allow to obtain the sets of textural features characterizing individual tissues and their condition [1].

The most effective method for automating the classification of the medical images' texture is the use of artificial neural networks. It allows creating the diagnostic systems that achieved much better results in comparison tests than doctors. The use of neural networks to interpret data derived from the analysis of image features, allows for the accurate classification of the examined tissues. It increases the detectability of even small, hardly perceptible pathological changes in the organs [2, 3].

Problem statement

The texture is defined as a complex visual pattern containing elements with a specific brightness, color, shape and other common features. The properties of these elements correspond to the visual impressions associated with a certain regularity, roughness, roughness, smoothness, graininess, directionality and other similar features [3, 4].

The texture is also defined as the distribution of the brightness of the image's points in its defined area. Characterization of the texture of this area involves determining the rules for the organization of its distribution [3].

The distribution defining the structure of the imaged organs and tissues depends on the physical phenomenon used in the imaging process. For magnetic resonance images, the brightness assigned to each pixel depends on the values of the time constants T1 and T2, respectively. In contrast, in images from a CT scanner, pixel brightness values determine the degree of X-ray absorption in tissues. The proper resolution of the image obtained plays an extremely important role in correctly illustrating the properties of the texture. The main rule is to keep the size of pixels or voxels much smaller than the smallest texture elements. The higher the image resolution of the examined structures, the more texture features can be determined [5].

There are four main approaches to the extraction of textural features in the literature. These are statistical methods, mathematical models (mainly autoregression and fractal models), transformational methods (wavelet transform, Gabor filters) and a structural approach in which the basic, repeating element of texture (so-called teksel) is searched for and the rules of its distribution are determined.

Visual results of anatomical structures are characterized by a specific distribution of brightness levels and are seen as homogenous areas. Characterization of the texture of this area involves determining the rules of its distribution [6].

Analysis of recent research and publications

Currently, there are many methods for acquiring image data of the human body. These methods are selected depending on the structures of the image we would like to obtain. Depending on the technique and the physical phenomenon used, the more or less accurate texture analysis and interpretation of the received information is possible [3, 6].

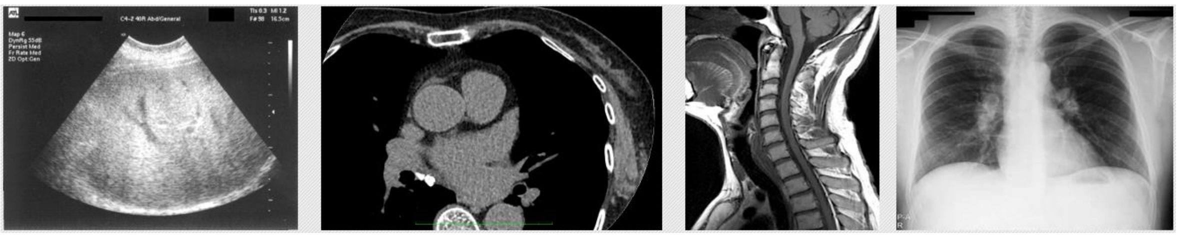

Fig. 1. Medical images: USG, CT, MRI, RTG [3]

Methods of image texture’s analysis combined with appropriate classification algorithms are widely used in the diagnosis of internal organs’ diseases depicted by various methods. An example of such an application may be the diagnosis of benign and malignant microcalcifications on breast mammography images (X-rays) [7, 8, 9], classification of lung diseases [10], identification of varieties of malignant brain tumor (magnetic resonance) [11, 12], classification of thyroid diseases [13] and detection of focal lesions in the liver (computed tomography) [14, 15].

The purpose of the study

Examination of image textures that are a diagnostic material involves determining the specific parameters and features characterizing the examined tissue or internal organ. Based on them, the classifiers are established. Thanks to the structure of artificial neural networks, the classification process allows the use of many data obtained during the analysis of medical images [3, 16].

The supervised classification is the most frequently used one. In this case, it is necessary to prepare a training set that will be used to generate classifiers. Establish the set of textural features that will create a vector for the training set. These types of collections are created based on a database of images already classified. After "teaching" the classifier, the system can be used in the process of identifying new, undiagnosed cases [3, 17].

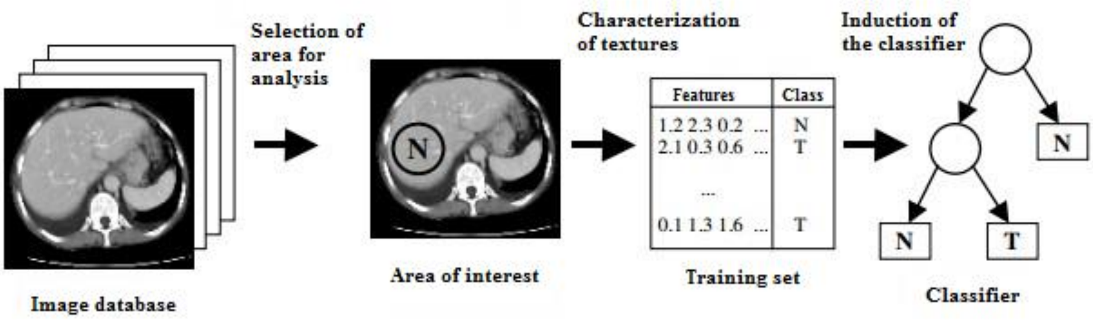

Fig. 2. The process of building a classifier based on a processed image database [1]

The main goal is to assign the analyzed area to one of two basic groups: as healthy tissue or tissue with pathological changes. This is the simplest division, providing information on the occurrence of changes. Further analysis of the changed tissues texture are to determine the type and the severity of pathological changes [17, 18].

Presentation of the main material

Depending on the method used to obtain the image, the pre-processing should be selected appropriately. To avoid changing the essential features of the image, the processing operations are limited to several procedures necessary for further action. They involve separating regions of interest, converting samples from RGB to grayscale and normalizing the range of brightness of the images.

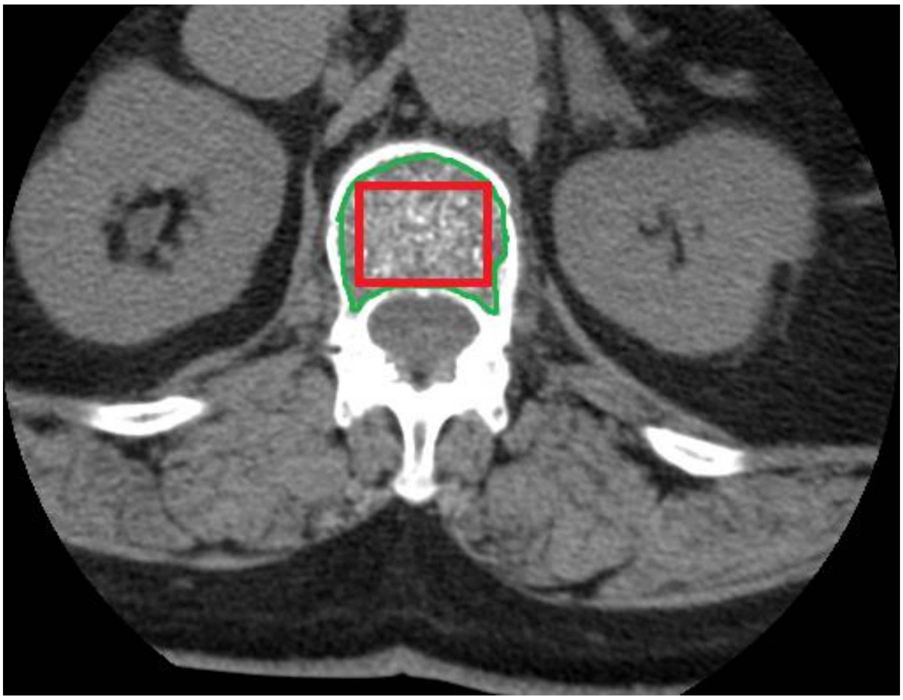

Fig. 3. CT of the spine with ROI

Each of the samples should have the same size and represent the same type of tissue.

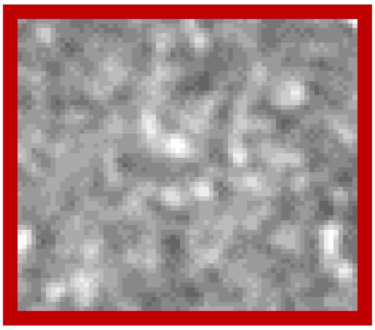

Fig. 4. Texture of the cancelous bone

The results of the analysis of textures from CT and magnetic resonance images available in the literature showed the possibility of a statistical approach to the extraction of traits [3, 17, 18]. The MaZda program (version 4.6) is a tool to apply to this approach. This program allows analyzing gray texture areas and determining numerical values for 283 image features.

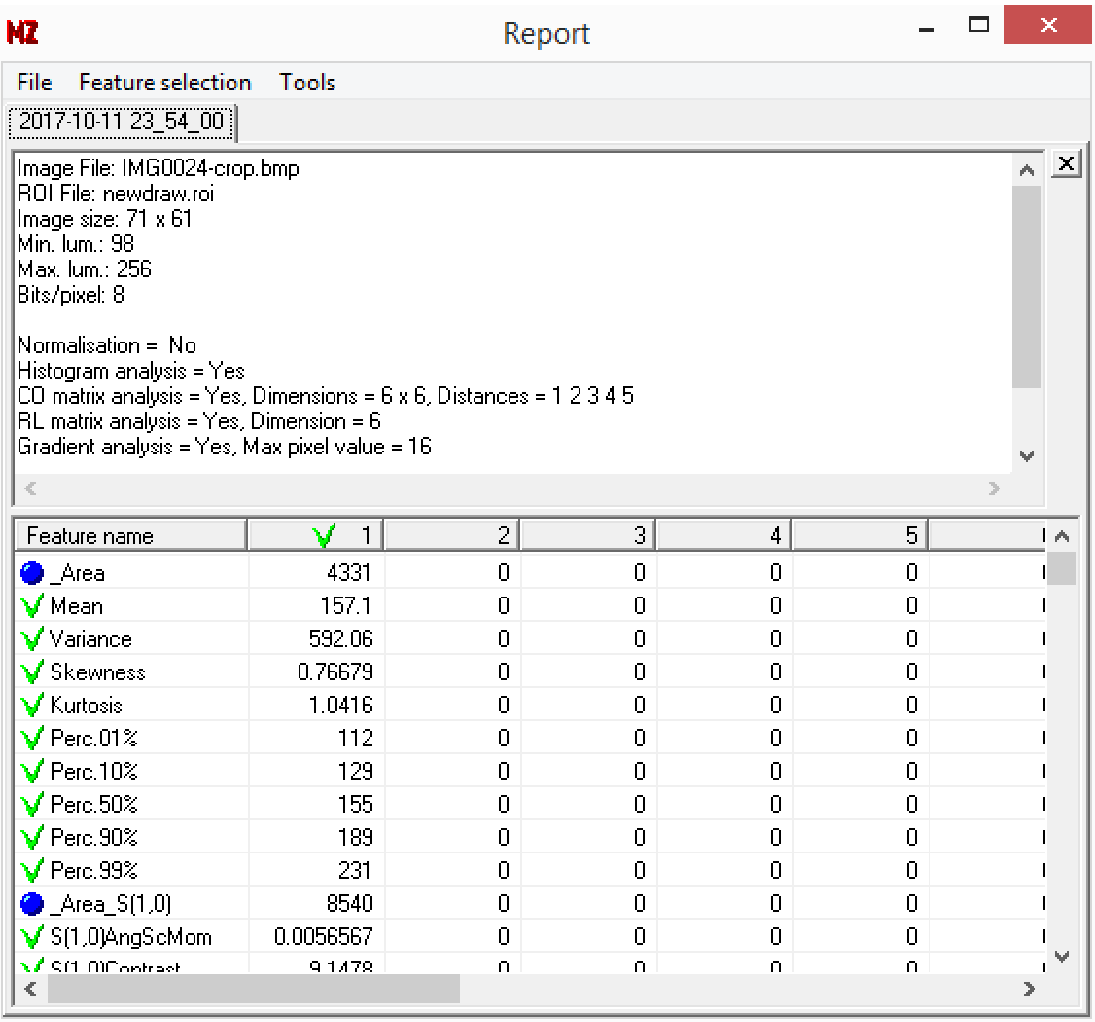

Fig. 5. Characteristics report obtained using the MaZda program

The obtained features and ranges of their values for healthy tissues and patients should be reduced. The first step is the elimination of features containing information that is useless from the point of view of classification. These are the features with the constant value in all observations.

Feature reduction is carried out in the process of extraction and selection. The selection of discriminatory features involves choosing a certain group of them from a set of original features. Extraction is aimed at constructing new features, created by linear or nonlinear transformations of the obtained set.

After the feature reduction, the construction stage of classifiers takes place. In medical images' texture analysis, the supervised classification method is generally used, that is, teaching with the teacher. There are two stages of this method application. The first stage is the discrimination. It involves building a model based on the training set. The second stage, classification is the allocation of samples to the appropriate classes indicated by the model.

Neural networks have the ability to learn, i.e. the ability to independently adjust weighting factors. Network 'teaching' involves extorting the specific reaction to the input signals. The aim of 'teaching' is to select the weights in particular neurons so that the network can solve the problems posed [19].

Supervised 'teaching' is done under the supervision of an external "teacher". This determines the information that should appear on the network output for the example given at the input. In the case of texture analysis, it is information whether the sample presents healthy tissue or tissue with pathological changes. The next step is to check if the response from the network is correct. If correct then no action is required, if not, the weight changes. The process is repeated until the correct network response is received [20].

In subsequent learning cycles, the network selects the scales in such a way that its answers are as accurate as possible with the learning patterns. An important feature of this process is the existence of feedback, allowing the correlation of weights in the network [20]. The distance between the actual and desired network response is a measure of the error used to correct network parameters. Often the learning set is the implementation of an accidental process and the error minimization procedure must consider its statistical properties. As a result, most of the learning algorithms with the teacher comes down to statistical error minimization in the multidimensional space of weights [19, 20].

After conducting the process of training of the neural network, its operation is checked. Literature reports determine the effectiveness of the resulting systems at the level of 93% [3, 11, 19, 20]. The chances of achieving the best results increase along with the collection of training samples and the extension of the "teaching" time. Thanks to these tools, the effectiveness of the diagnostic process increases, and identifying even small pathological changes in the examined tissues is possible.

Summary

The characteristics of medical image textures is an important complement to information on the tissues and structures examined, especially in the case when the pathological changes are detected in the examined organs. The visual assessment does not always allow for precise and accurate diagnosis. For this reason, computer image analysis methods are additionally used to allow for accurate examination of the image distribution and any, even slight, irregularities in the texture. Classification methods using complex structures of artificial neural networks allow to determine not only the occurrence of pathological changes in tissues, but also to assign them to a given disease and the degree of its severity.

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РЕЗЮМЕ

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Використання нейромереж для класифікації текстур медичних зображень

Одним з найважливіших джерел діагностичної інформації є зображення внутрішніх органів. Ключовим питанням в процесі обробки комп'ютерних зображень є чіткий та об'єктивний опис областей, які на них походять, що називаються регіонами інтересу (ROI). Найефективнішим автоматизованим методом класифікації текстури медичних зображень є використання штучних нейронних мереж. Використання нейромереж для інтерпретації даних, отриманих з аналізу властивостей зображення, дозволяє точно класифікувати досліджувані тканини.

Розподіл, що визначає структуру зображених органів та тканин, залежить від способу отримання зображень. Правильна роздільна здатність відіграє надзвичайно

важливу роль при ілюструванні властивостей текстури. Візуальні результати анатомічних структур характеризуються специфічним розподілом рівнів яскравості і розглядаються як однорідні області. Характеристика таких текстур передбачає визначення правил розподілу.

Контрольована класифікація є найбільш часто використовуваною. У цьому випадку необхідно підготувати навчальну вибірку, яка буде використовуватися для генерації класифікаторів, налаштувати множину текстурних властивостей, яка сформує вектор для навчальної вибірки. Множини створюються на основі бази даних уже класифікованих зображень. Після навчання класифікатора, система може використовуватися в процесі виявлення нових, недіагностованих випадків. У подальших навчальних циклах мережа вибирає масштаби таким чином, щоб її відповіді були максимально схожими із моделями навчання. Відстань між фактичною та бажаною мережевою відповіддю є мірою помилки, яка використовується для корекції параметрів мережі.

Використовуючи контрольовану класифікацію та налаштування навчальної бази, можна досягти точності результатів класифікації на 93%. Шанси досягнення найкращих результатів збільшуються разом зі збором навчальних зразків та подовженням часу навчання.

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