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Based on Artificial Intelligence Neural Network CNN Method Analysis and Processing of Dynamic Optical Breast Lesion Images

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Abstract: Breast cancer is the most common cancer in women. At present, the methods of examining lesions are generally mammography, or B-scanning and other methods with certain radioactive sources, which may lead to aggravation of breast lesions in young women. The dynamic optical breast scanning method uses infrared light to avoid the harm of X-rays to the human body. According to current research, doctors can use Dynamic Optical Breast Image (DOBI) to determine whether a patient has breast cancer. Studies have shown that convolutional neural networks (CNN) have higher detection accuracy in determining whether a patient has breast cancer. In this paper, we use an artificial intelligence neural network approach to analyze and process dynamic optical breast lesion images: we model the clinical lesion breast images in 3D, and use the VoxelMorph algorithm to segment the 3D images into 2D images; The time, space, location, and pathological trend curves in the image are analyzed and processed. We compared classification, sensitivity, and specific characteristics with the original dynamic breast lesion image scoring analysis system. The experimental results show that the accuracy is improved. At the same time, the problem of the original system's signature in the ROI area and leaf curve is solved. The use of CNN improves the analysis and processing speed, shortens the processing time, and increases the accuracy of the diagnostic reference from 83% to 90%.

Keywords: Dynamic Optical Breast Lesion Image, Artificial Intelligence Neural Network, CNN Method

1. Introduction

Breast cancer has become the first killer threatening women's health. According to the latest data published by International Agency for Research on Cancer (IARC), female breast cancer accounts for 11.4% of the new cancer cases in the world in 2020, becoming the most diagnosed cancer in the world. There is no effective method to treat breast cancer, which is a worldwide problem in the field of medical research. However, many studies have shown that early observation and monitoring of breast images can greatly improve the early detection rate of breast cancer. With the development of computer-aided diagnosis technology, machine learning plays an important role in breast cancer monitoring. Predecessors have done some related work.

Anji Reddy Vaka et al. proposed a new method-Deep Neural Network with Support Value (DNNS) to evaluate the efficiency and performance. The experimental results show that the accuracy rate in the Dataset taken from the M. G Cancer Hospital and Research Institute is greater than 97% [1]. Huan-Jung Chiu et al. used Principal Component Analysis (PCA) for dimensionality reduction analysis, Multilayer Perceptron (MLP) Network for feature extraction, the last layer of MLP used transfer learning method, and finally Support Vector Machine (SVM) for classification. The accuracy reached 86.94%. This kind of fusion method has certain reference significance to the research [2]. Jayesh George Melekoodappattu suggested ELM with the Fruitfly Optimization Algorithm (ELM-FOA) along with GSO to regulate the input weight to achieve maximal performance at the hidden node of the ELM. The testing precision and sensitivity of GSO-ELM-FOA are 100% and 97.91%, respectively. The system developed will detect the calcifications and tumors with an accuracy of 99.15% [3]. Fayez AlFayez compared the two breast cancer detection methods-Extreme Learning Machine (ELM) and MLP, the results showed that ELM-based results were better than MLP-based ones with more than 19% [4].

The Dynamic Optical Breast Imaging (DOBI) is an effective method for young women [5]. It has a good potential for discriminating malignant from benign lesions, and has proved to be a low-cost, noninvasive technique [6, 7]. In our previous research, we further propose a more effective standards Criteria, and realized automatic recognition and classification to DOBI images [8]. A practical segmentation model is learned by customizing a neural network architecture for a certain task or dataset and training it from scratch [9-11]. Voxelmorph is a fast learning-based algorithm for deformable, pairwise 3D medical image registration from MIT [12]. Experimental results show that 3D U2-Net is capable of competing with traditional models in terms of segmentation accuracy [13].

In this paper, we combine Voxelmorph algorithm with CNN for the analysis of dynamic optical breast images [14], then we compare the classification, sensitivity, and specific characteristics with the original dynamic breast lesion image scoring analysis system. The experimental results show that the use of CNN improves the analysis processing speed, shortens the processing time, and improves the accuracy of the diagnostic reference from 83% to 90%.

(In which: data and samples are provided by DOBI company, we perform the second feature standard for the samples, and use the CNN network to train the model to get the results.)

The remainder of this paper is organized as follows. Section II introduces the DOBI technology. The main method is presented in Section III. Section IV shows the experimental results. Conclusions are drawn in Section V.

2. DOBI Technology

According to the Folkman tumor neovascularization theory, the size of breast cancer tumors that can be diagnosed clinically is two millimeters at the early stage (after the tumor neovascularization has developed to one centimeter size). DOBI's dynamic tumor blood vessel targeting technology distinguishes the different responses of vulnerable tumor capillaries and normal tissue capillaries to blood flow: tumor capillaries are congested and consume a lot of blood oxygen over time. The congestion volume and blood oxygen consumption of tumor neovascularization is continuously monitored by near-infrared fluoroscopy and collected with a highly sensitive charge coupled device (CCD). The collected data is processed and reconstructed by using diffraction optical tomography (DOT) to display the blood volume and metabolic rate of new blood vessels of breast tumors in the form of four-dimensional full breast functional images as shown in Figure 1.

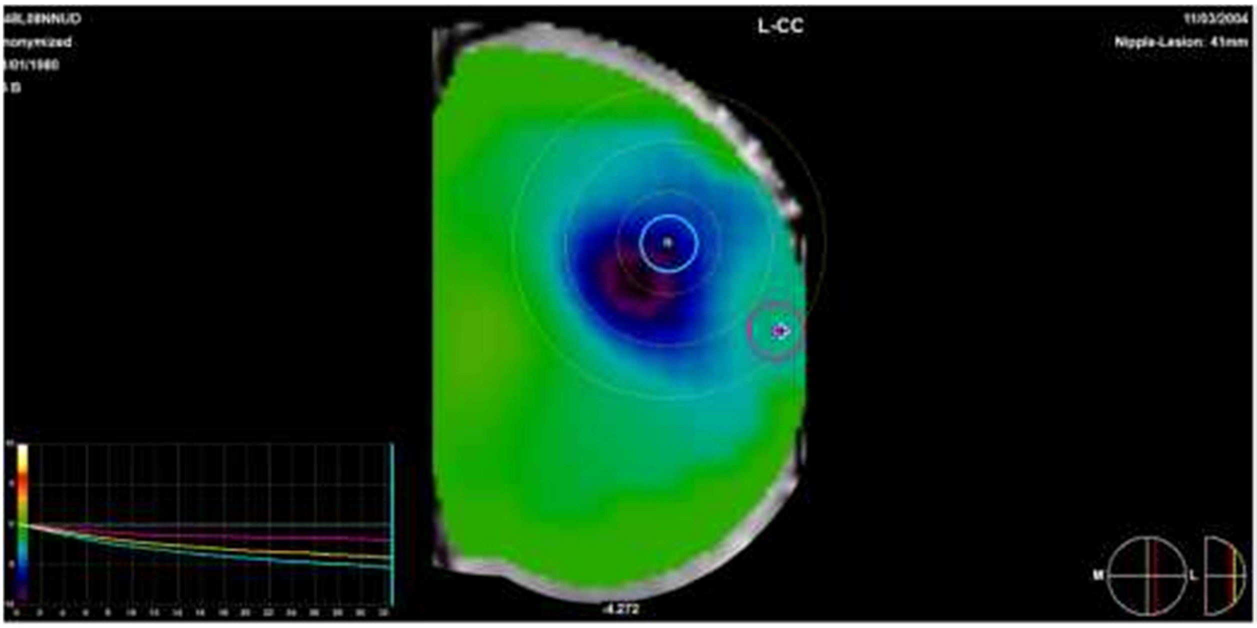

Figure 1. *DOBI image.*

The DOBI methodology is "a computer with knowledge and experience looking for malignant features with the size of several centimeter around a tumor of several millimeters in the breast" [15]. Because by using DOBI technology, people can detect breast cancer 6 to 8 years as early as traditional methods clinically, DOBI is clinically adopted for early detection of breast tumors (2-20 mm). It can make up for the limitations of early diagnosis (invisible by mammography or ultrasound) and fill the gap in breast screening (invisible by mammography or ultrasound).

The main imaging principles of DOBI are as follows: first, distinguish tumor blood vessels and normal blood vessels by dynamic pulse pressure, then detect only the new blood volume and metabolism process around the breast tumor by near-infrared imaging, and finally display the blood volume and metabolic rate of new blood vessels of breast tumor by four-dimensional full breast image. It should be noted that infrared light imaging has a certain penetration ability to objects. Human soft tissues, such as fat, fiber and muscle, have strong penetrability, and the degree of penetration is related to its density. Hemoglobin can absorb the nano light. When the nano light penetrates through the human tissue, the absorption of hemoglobin will produce shading shadow. Infrared light has different penetrability to hemoglobin in blood. Hemoglobin has strong absorption to nano light, while water and fat (55% + 20%) have low absorption to nano light, which can effectively distinguish the characteristics of cancer.

By using DOT, we can analyze the biological information of breast transillumination and detect changes in light absorption in the tissue. The change of blood volume shows aggregation characteristics and the change of blood oxygen content shows the metabolism rate. DOT is very sensitive to the unique changes in blood volume and high metabolic rate associated with the formation of new blood vessels in the breast. Use infrared fluoroscopy, dynamic pressure, continuous measurement and DOT, and judge the impact on the formation of new blood vessels by applying pressure. Slight pressure stimulation is adopted to create the difference between normal and new blood vessel formation areas, and dynamically distinguish the blood in benign and malignant tissues. If there is no light absorption and the pressure makes the normal capillary bloodless, it is a normal capillary. If the deformation caused by pressure blocks the new blood vessels, congestion will occur, proving the possibility of cancer.

At present, the classification of cancer features is mainly realized by manual comparison and scoring by experienced doctors. The original dynamic breast lesion image scoring analysis and processing system is a dynamic breast lesion inspection instrument-dynamic optical breast lesion image analysis and processing system that we helped DOBI research and develop. This system uses the automatic reference POR, point of interest PO, automatic edge state map MPS in the time, space, location, and lesion trend curve of dynamic breast lesions image, recognition algorithm to explore ROI, time state context features: signature curve similarity SCSI, and uses vector machine SVM classification to score, to help doctors realize the reference diagnosis of breast lesions. The method proposed in this paper realizes automatic classification and discrimination, reduces the difficulty of operation, and lays the foundation for the realization of comprehensive breast cancer screening.

3. Methodology

Taking 250 dynamic optical 3D images of breast lesions provided by DOBI company as research samples, we carry out 3D image modeling of clinical breast lesions and propose a new algorithm. The main processes are as follows:

3D modeling

We use Rhino to realize 3D lesion image modeling and VoxelMorph algorithm to generate real-time 3D medical images. VoxelMorph algorithm, which is a framework based on rapid learning for deformable pairwise medical image registration. Traditional registration methods optimize the objective function for each pair of images, which may be very timeconsuming for large data sets or rich deformation models. By contrast, based on recent learning-based methods, VoxelMorph algorithm formulates the registration as a function of mapping the input image pairs to the deformation fields that align these images. The function is parameterized by the convolutional neural network, and the parameters of the neural network are optimized on a set of images. Given a new scan pair, VoxelMorph quickly calculates the deformation field through a direct evaluation function. In this paper, using the auxiliary segmentation available in the training data, we have proved that the accuracy of the unsupervised model is comparable to that of the latest methods, while the computational speed is orders of magnitude faster. At the same time, VoxelMorph trained with auxiliary data can improve registration accuracy during testing and evaluate the impact of training set size on registration. This method is expected to speed up the medical image analysis and processing process and promote novel directions in learning-based registration and its applications.

2D image conversion

The 3D image is segmented and converted into a 2D image, and the time, space, location, and pathological trend curve in the image are analyzed and processed by CNN. The use of infrared dynamic breast lesions equipment to perform imaging examinations of women's breasts can avoid damage to the diseased organs caused by the use of X-ray equipment. However, because the X-ray film itself is a 2D image that overlaps with other tissues, the tissue structure often obscures the disease, which seriously affects the accuracy of the doctor's diagnosis of the disease. At present, the radiation dose of infrared dynamic breast lesions equipment for the imaging examination of women's breast is basically zero, so that the scope of application is wide. In this paper, we use CNN to decompose different parts of 2D infrared breast lesions image by using the structured image knowledge of unpaired 3D infrared dynamic image, and then highlight the image details of a certain part to obtain enhanced image. It can achieve:

Different from traditional domain knowledge transfer methods that rely on paired data, the proposed method can effectively use the anatomical structure knowledge of 3D infrared dynamic breast images to achieve accurate decomposition of unpaired image slices;

The enhanced image can be used for automatic disease classification, and under the same test conditions, it has achieved a disease classification accuracy rate exceeding the best method in the industry.

The 3D U2-Net framework is adopted to segment the lesion image: organ tissue and lesion area segmentation is one of the important contents in medical image analysis. Traditional methods usually need to establish a separate segmentation for each organ and each modality. When faced with a new segmentation task or image modality, it is usually necessary to retrain and design the segmentation network, which lacks universality. To this end, we designed a more universal segmentation model, using a model to achieve adaptive target segmentation under multi-organ and multi-modal conditions (as shown in Figure 2). The main ideas are as follows:

Based on the idea of separable convolution, a domain adapter is designed, which is composed of channel-by-channel convolution and point-by-point convolution. Channel-by-channel convolution is used to extract domain-specific features and point-wise convolution is used to extract shared features between domains. Using U-Net 3D as the skeleton network, replace its standard convolution with the above-mentioned domain adapter to form a universal segmentation network structure for multi-domain segmentation;

Introduce a round-robin method to implement a universal segmentation model training framework based on multiple data sets;

The universal segmentation model we obtained on the five human organ data sets has achieved a segmentation accuracy equivalent to that of the traditional independent model, but the amount of model parameters is significantly reduced, only 1% of the latter;

The above mentioned universal model can be well transferred to the task of new data set, which shows its strong promotion ability.

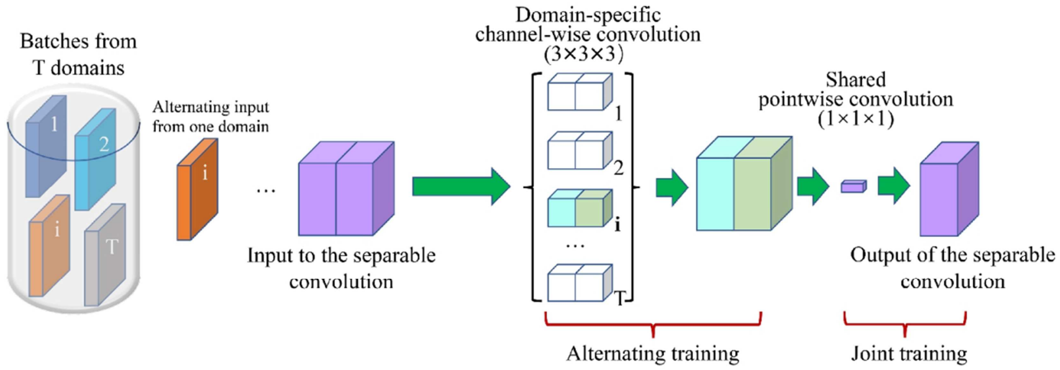

Figure 2. *3D U2-Net.*

The convolution neural network process as shown in Figure 3 are as follows: input 250 lesion samples, as defined: automatic reference POR, point of interest PO, automatic edge state map MSP, recognition algorithm to explore the area of interest ROI, time state context characteristics: signature curve similarity SCSI [1] and other analysis and processing.

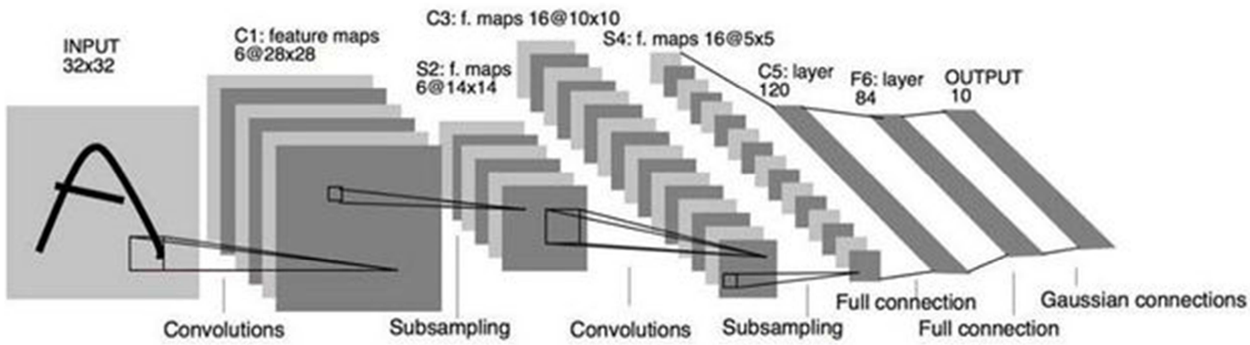

Figure 3. *Neural network CNN.*

Realization of time features

According to the classification criteria of related features, we have programmed and judged and whether there are fluctuations by the time difference value of the point of interest in the shape of the time curve; whether it is linear decline by calculating the Pearson correlation coefficient of time curve and linear curve, etc. It should be noted that the Pearson correlation coefficient is a statistic used to reflect the degree of linear correlation between two variables. The Pearson correlation coefficient of two continuous variables (X, Y) is equal to the covariance between them divided by the product of their respective standard deviations. The formula is as follows:

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma X \sigma Y} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E^2(X)}\sqrt{E(Y^2) - E^2(Y)}} \tag{1}$$

The value of the coefficient is between -1 and 1. A coefficient of 0 means that there is no correlation between the two variables. 1 or -1 is a strong correlation, in which 1 is a positive correlation and -1 is a negative correlation. Usually the value of coefficient between 0-0.2 is called no correlation or very weak correlation, 0.2-0.4 is weak correlation, 0.4-0.6 is medium correlation, 0.6-0.8 is strong correlation, and 0.8-1.0 is very strong correlation.

Realization of background features

First compare the time curve with the background curve as a whole, if the value of Pearson correlation coefficient is greater than 0.8 (very strong correlation), judge them as similar; if it is less than 0.3, judge them as irrelevant; if it is between 0.3 and 0.8, judge them as uncertain. For this type of data, we use the method of classifying the curve, divide the time and the background curve into three sections, and compare them section by section (using Pearson correlation coefficient) as shown in Figure 4.

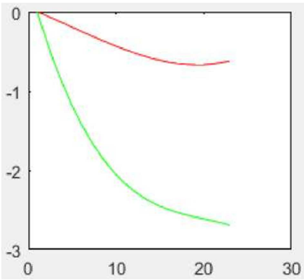

Figure 4. *Red is the background curve, green is the time curve.*

Feature scoring

1) *Time curve scoring:* the time curve is divided into five grades according to its shape, namely:

The curve is all upwards, 0 points;

The curve has ups and downs, 1 point;

The curve drops slightly (-1 to -3), 3 points;

The curve drops rapidly (the amplitude is greater than 2 and does not reach the level of a straight line), 5 points;

The curve is straight down, 7 points.

2) *Segmentation curve scoring:* the segmentation curve is similar to the time curve scoring, but is slightly different in amplitude:

The curve is all upwards, 0 points;

The curve has ups and downs, 1 point;

The curve has a small drop (less than 2), 2 points;

The curve drops rapidly (the amplitude is greater than 2 and does not reach the level of a straight line), 3 points;

The curve is straight down, 4 points.

When judging background features, first we should judge the type of curve, that means judge whether the time curve and the background curve are the same type, for example, the same type of undulation. If they are different types, they are not similar (whether the whole or segment); if they are the same type, judge the degree of similarity between them; if the similarity is very high, then judge them to be similar, if it is not high, judge the similarity and dissimilarity. Here you need to pay attention to subdividing the curve in the slow descent category (regardless of the whole or segment), subdividing it into straight descent and non-straight descent, and then judge the similarity.

The similarity score of the overall curve is 0 for similarity, 4 for dissimilar, and 2 for uncertain; the segmented curve is similar to it, and the scores are slightly different: 0 for similarity, 3 for dissimilar, and 1 for uncertain.

4. Research Result

Using 250 women DOBI-Comforscan scan samples, through the image of time, space, location, and pathological trend curve using neural network CNN for image analysis and processing. The results were compared with the classification, sensitivity, and specific characteristics of the original dynamic breast lesion image scoring analysis system, Experiments show that: We compared the classification, sensitivity and specificity features, the sensitivity increased from 91% to 95%, and the specificity feature increased from 71% to 85%. At the same time, the signature problem of the original system in the ROI area and the leaf curve is solved. The use of CNNs increased the speed of analysis and processing, shortened the processing time, and increased the accuracy of the diagnostic system reference from 83% to 90%.

5. Conclusions

In this article, we use an artificial intelligence neural network approach to analyze and process dynamic optical breast lesion images: we model the clinical lesion breast images in 3D and use the Voxel Morph algorithm to segment the 3D images into 2D images; The spatial, location and pathological trend curves were analyzed and processed. Experiments show that: We compared the classification, sensitivity and specificity features, the sensitivity increased from 91% to 95%, and the specificity feature increased from 71% to 85%. At the same time, the signature problem of the original system in the ROI area and the leaf curve is solved. The use of CNNs increased the speed of analysis and processing, shortened the processing time, and increased the accuracy of the diagnostic system reference from 83% to 90%.

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