Automated assessment of breast tissue density in non-contrast 3D CT images without image segmentation based on a deep CNN

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ABSTRACT

This paper describes a novel approach for the automatic assessment of breast density in non-contrast three-dimensional computed tomography (3D CT) images. The proposed approach trains and uses a deep convolutional neural network (CNN) from scratch to classify breast tissue density directly from CT images without segmenting the anatomical structures, which creates a bottleneck in conventional approaches. Our scheme determines breast density in a 3D breast region by decomposing the 3D region into several radial 2D-sections from the nipple, and measuring the distribution of breast tissue densities on each 2D section from different orientations. The whole scheme is designed as a compact network without the need for post-processing and provides high robustness and computational efficiency in clinical settings. We applied this scheme to a dataset of 463 non-contrast CT scans obtained from 30- to 45-year-old-women in Japan. The density of breast tissue in each CT scan was assigned to one of four categories (glandular tissue within the breast <25%, 25%–50%, 50%–75%, and >75%) by a radiologist as ground truth. We used 405 CT scans for training a deep CNN and the remaining 58 CT scans for testing the performance. The experimental results demonstrated that the findings of the proposed approach and those of the radiologist were the same in 72% of the CT scans among the training samples and 76% among the testing samples. These results demonstrate the potential use of deep CNN for assessing breast tissue density in non-contrast 3D CT images.

Keywords: 3D CT images, breast tissue density assessment, breast region localization, deep CNN

1. INTRODUCTION

Breast density determined via mammography is suggested to be an efficient and effective indicator of breast cancer risk in women [1]. The conventional method classifies mammographic breast density into four categories (glandular tissue <25%, 25%–50%, 50%–75%, and >75% within the breast) for the purpose of further diagnosis or treatment. This assessment can be performed easily and more efficiently in 3D CT images (Fig. 1), which are widely used for chest cancer screening and many other diagnostic purposes [2]. Computer-based CT image segmentation is an accepted pre-processing step that enables quantification of the volume and density of the mammary glands for predicting breast cancer risk. However, the development of a robust and accurate mammary gland region segmentation process for CT images is ongoing. Although some previous works have reported segmentation of the mammary gland region [3,4], the development of fully automated segmentation of mammary glands in non-contrast CT images remains challenging due to

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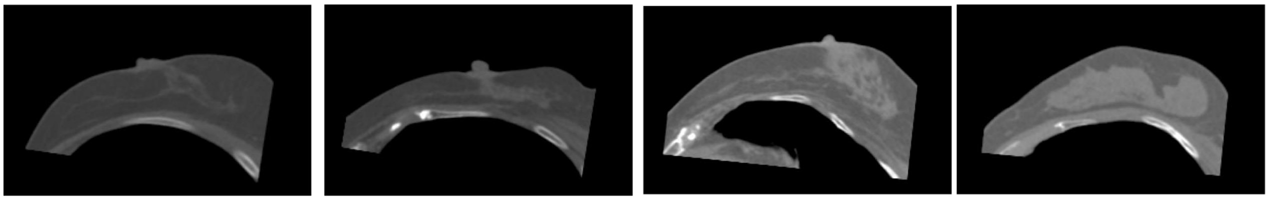

Fig.1. Typical sections of breast regions in 3D CT cases showing four categories of breast density. From left to right, glandular tissue within the breast <25%, 25%-50%, 50%-75%, and >75%. [5]

low CT image contrast between the internal soft tissues of the breast regions, irregular shapes among mammary glands, and large variations in volume among different patients and age groups. An assessment of breast density in non-contrast CT images without segmentation of the breast region is expected as the standard measure in clinical medicine.

In our previous work [3], we proposed an approach for segmenting mammary glands by first recognizing and removing the tissues (such as skin, muscle, fat, and ribs) around the mammary glands, and then measuring the density in the remaining regions in 3D CT images. A similar approach [4] for segmenting the breast region has been proposed for low-dose CT images. However, the robustness of segmenting multiple tissues around the mammary glands is inadequate because the stringent conditions required for the successful segmentation of related tissues, and the poor performance of a number of ad-hoc functional-overlapped algorithms based on human experience. Although we proposed a straightforward approach for the segmentation of mammary gland regions via machine-learning in our recent work [5], a method that can bypass the segmentation of mammary gland regions in 3D CT images and directly classify breast densities is strongly desired.

In this paper, we propose an automatic scheme for the assessment of breast densities in 3D CT images without segmentation. Compared with conventional methods, the advantage of our approach is that we can bypass mammary gland region segmentation [3-5] and directly classify breast densities in 3D CT into the four categories used in clinical medicine. The proposed scheme is an extended and improved version of our previous work [5]. This work innovatively introduces a deep CNN into our framework for the classification of breast density and uses deep learning to enhance efficiency and reduce computational costs. We have outlined our proposed scheme and described our methods in the following sections. The experimental results obtained for 463 non-contrast CT images are illustrated and discussed in the final section.

2. METHODS

2.1 Outline

The process flow of the proposed method is shown in Fig.2. Our scheme for the automatic assessment of breast density in non-contrast CT images includes two steps: (1) "breast region localization" and (2) "breast density classification". The algorithms of the two steps were designed separately based on data-driven, machine-learning approaches, and executed sequentially during the assessment of breast density. In step 1, we used an object detection technique based on a supervised learning approach [3] to detect the minimum-bounding rectangle (MBR) of the left or right breast regions in 3D CT images. In step 2, we used a deep convolutional neural network (CNN) based on a supervised deep learning approach to classify the CT image inside the MBR into one of four categories, each of which represents a different type of breast density according to clinical expectations. The details of each step are described in the following sub-sections.

2.2 Breast region localization

The location of a breast region was defined as a 3D MBR with an orientation that included all voxels of the breast region and as few voxels of other tissues as possible. A 3D MBR was represented by six coordinates of two corner points and two angles showing the orientation of the rectangle in a 3D image space. The localization process estimated the coordinates in a 3D CT case automatically. We have developed a universal framework for the localization of several organ types in 3D CT images in our previous work [5-7]. The method used in this framework can be likened to a window sliding and matching to scan all positions in a 3D CT case and exposing the MBR of a special target in an ad-hoc feature (selected image textures) space [8, 9]. This space was learned from a known CT image dataset, and can be optimized

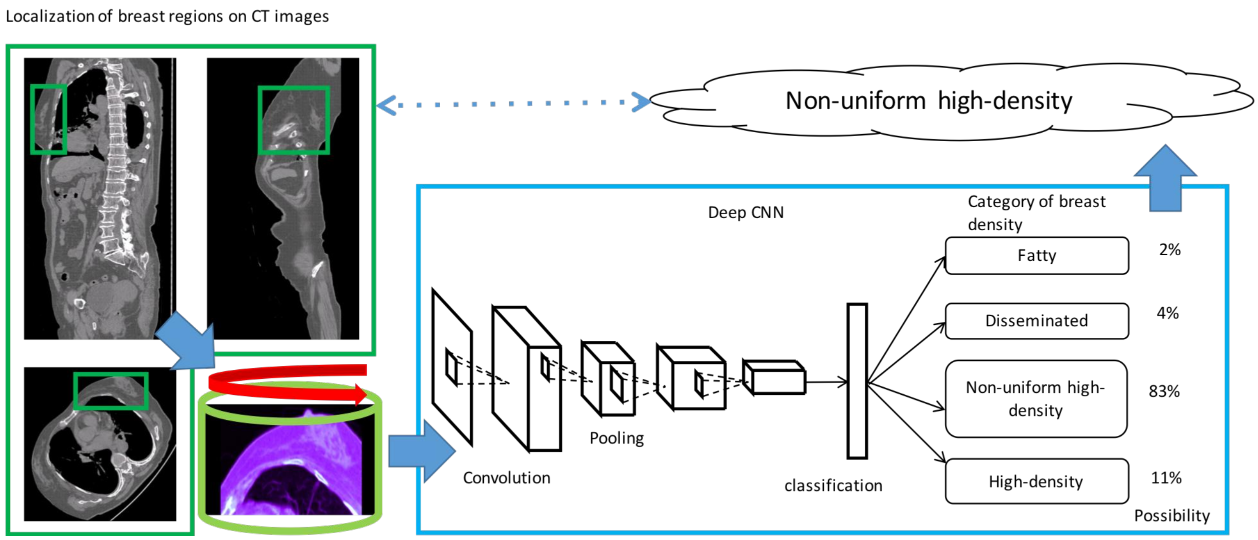

Fig.2. Flow process of the proposed approach for the automatic assessment of breast density in 3D CT. The definitions of the categories are based on the glandular tissue within the breast (see Fig. 1).

specifically to distinguish a target organ (left or right breast region in this work). The details of breast region localization in 3D CT are described previously [5].

2.3 Breast density classification

The classification of breast densities in CT images was accomplished by using deep CNNs that were originally proposed for the classification of 2D color pictures [11]. A deep CNN structure, AlexNet [12], was used in this work. We trained this network by using several CT cases with the ground truth (the category number of breast density in each CT case) from scratch. Because the image format of inputs for AlexNet is in 2D color, we first converted each 3D CT case into several 2D color images, and made the final decision by voting on the classification results of individual 2D color images from the same 3D CT case. The training and testing details for the deep CNN are described in the following steps:

(1) Pre-processing: For an input CT case, a 3D region of interest (ROI) was first cropped from a 3D CT case based on the MBR of a breast region, and resized to a fixed image size by linear interpolation. We subsequently sampled 360 radial (2D) sections with equal intervals (angles) based on a cylindrical coordinate system with the origin at the nipple position and the axial orientation as the normal vector of the 3D body surface within the ROI. The CT number of the 3D CT cases (1 channel with a gray level of 12 bits) was decomposed into 3 channels (each channel had a gray level of 8 bits) by using contrast transformation with different parameters (image levels and windows). These three channels were used directly as Red-Green-Blue channels to generate a color map (like natural pictures) for training and testing the AlexNet.

(2) Training the deep CNN using CT images: The ground truth (human annotated category label) of breast density in each 3D CT case was attached directly to all 2D sections of the 3D breast region generated in step 1. We shuffled the 2D color maps for all 3D CT cases in a training dataset as the training samples. The training process repeated feed-forward computation and back-propagation to minimize the loss function, which was defined as the difference between the predicted category label of breast density and the ground truth annotated by a radiologist. The gradients of the loss were propagated from the end to the start of the network, and the method of stochastic gradient descent with momentum was used to refine the parameters of each layer.

(3) Testing the deep CNN of an unseen CT case: Our scheme used the same method as that in step 1 to decompose the 3D breast region into 2D sections (color maps) and passed each 2D section to the deep CNN to predict a category label that the current 2D section belonged to. For each CT case, we sampled 360 sections and received 360 labels (proposals) from the deep CNN for breast densities. We summarized all of the proposals belonged to 4 category labels, and the mode of the distribution of proposals was regarded as the final decision.

3. EXPERIMENT AND RESULTS

We applied the proposed approach to the classification of breast density in 3D CT images with the aim of predicting a risk of breast cancer in the future. A dataset that included 463 non-contrast torso CT scans, that distributed equally from 30- to 45-year-old-women, was used to evaluate performance. These CT scans were collected at Gifu University Hospital by two multi-slice CT scanners (LightSpeed Ultra16 of GE Healthcare and Brilliance 64 of Philips Medical Systems). Each CT scan followed a protocol (120 kV/Auto mA) and covered the whole human torso. The 3D CT scans had approximately 800–1200 axial CT slices by an isotopic spatial resolution of approximately 0.6–0.7 mm and a density (CT number) resolution of 12 bits. All CT images were obtained from patients with confirmed or suspicious abnormalities.

We manually annotated the MBRs of the left breast region in all CT images for evaluation. A radiologist (a specialist in interpreting breast cancer) classified the density of the left breast region in all CT cases into four categories (labeled 1 to 4) as the ground truth (GS). For localization of the breast regions on the CT images, we used the parameters learned from another dataset in our previous work [5], and directly applied the trained network to the dataset used in this study without any adjustments. The deep CNN for breast density classification was trained and tested based on the CT cases from scratch. We randomly selected 58 cases for testing, and used the remaining cases for training the deep CNN. The original parameters [12] used for training the AlexNet on natural pictures were used in this work. The learning curves based on 2D sectional CT images are shown in Fig. 3.

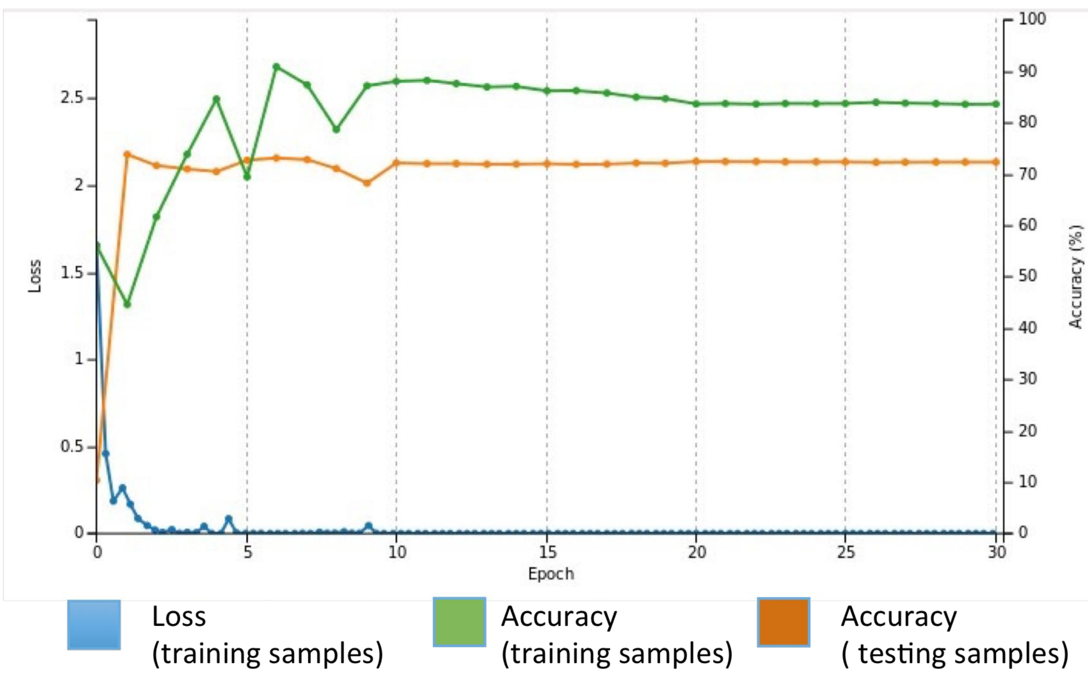

Fig.3. The learning curves for training a deep CNN for the classification of breast density in CT images.

The overlap ratio of MBRs between human annotation and localization results was used for localization of the breast region. The true positive rate of the classification of breast density was used to evaluate accuracy. Examples of successful and unsuccessful cases of breast localizations are shown in the upper part of Fig. 4. Three examples of breast density classifications (categories 2, 3, and 4) in successful and (categories 1, 2, and 3) in unsuccessful cases are shown at the bottom of Fig. 4. The 2D sampling results from two 3D CT cases are shown in Fig. 5.

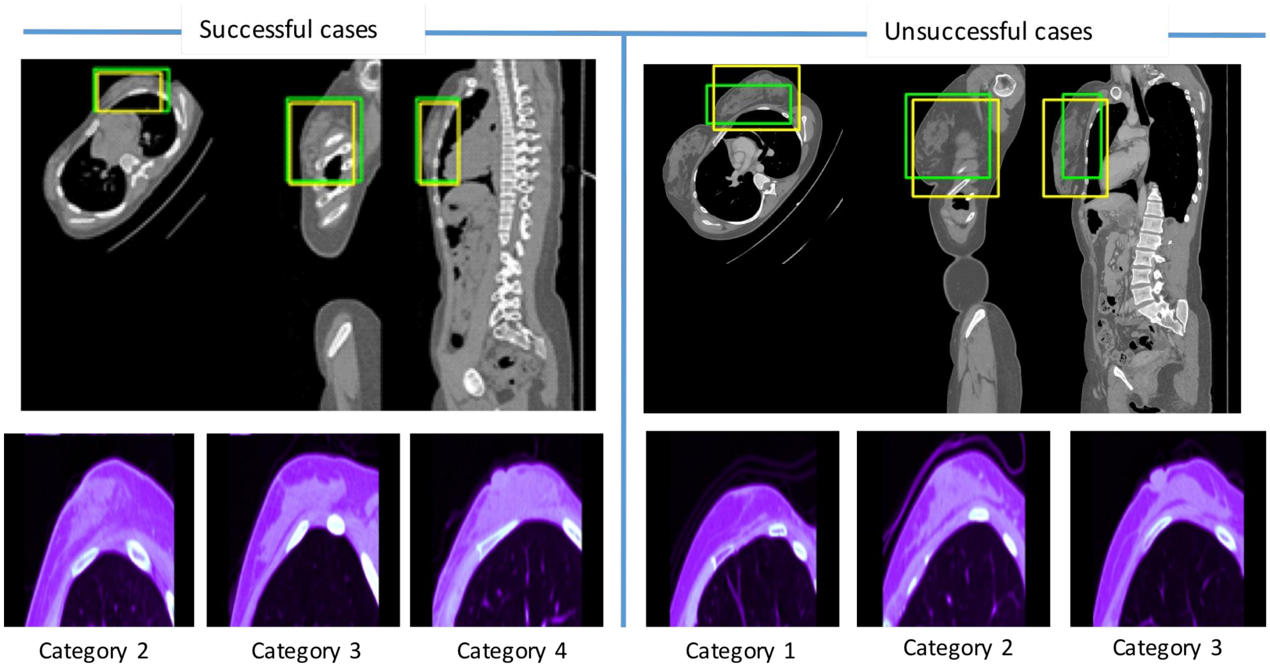

Fig.4. Examples of breast localization and density classification. Left side: successful cases; Right side: unsuccessful cases. Upper: the results of breast localization (green) and ground truth (yellow); Bottom: density classification.

The proposed scheme used both CPU and GPU to achieve breast density classification with a computational time of about 30 seconds per CT case (CPU: Intel Core i7 975, 3.33 GHz, GPU: NVidia TITAN X 12GB). A software package, CAFFE [13], was used for development based on the CUDA library [14] from NVidia Corporation.

4. DISCUSSION AND CONCLUSION

The major parts between the detected 3D rectangle and the ground-truth MBR were used as criteria (the overlapped region was more than two-thirds the volume of the MBR) for judging successful breast localization. We found that the trained breast region localization from our previous work [5] also worked well on the dataset in this work, and confirmed that left breast regions in 97% of CT cases were localized successfully. The detected bounding rectangles of breast regions in the unsuccessful cases (right side of Fig. 4) included parts of the mammary gland regions and could be used as deep CNN inputs for further classification of density.

For the classification of breast densities in the MBRs, we confirmed that the loss of prediction via AlexNet showed a quick convergence (within 3 epochs) to a small value (tending to zero) during the training stage; in contrast, the classification accuracy in testing samples (for validation purposes) showed convergence, and good performance was maintained at 72%. This result demonstrated that the useful parameters of AlexNet were successfully learned based on our dataset, and the trained AlexNet could classify breast density correctly in 72% of the 2D sections from 3D CT cases. After integrating individual 2D classification results with the relevant 3D CT case, the accuracy of the category

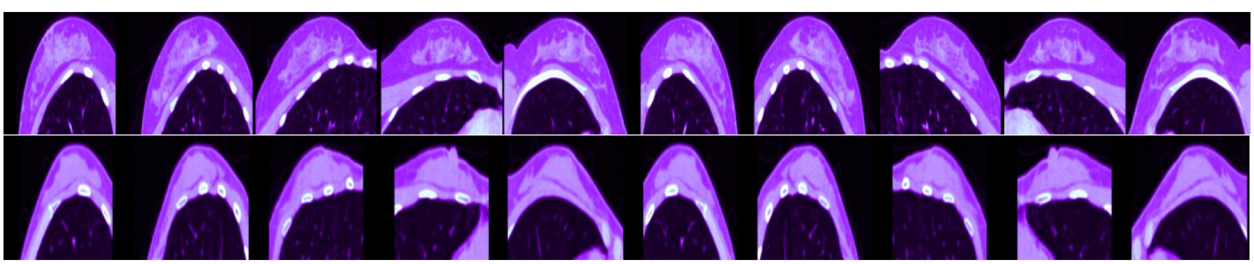

Fig.5. Ten radial (2D) sections sampled at an angle of 36 degrees from 3D breast regions in two 3D CT cases belonging to categories 2 (upper) and 3 (bottom).

assessments increased to 76%. This result demonstrated that our method—selecting the majority (mode value) of classification results on multiple 2D sections—enhanced the accuracy and robustness of the breast density assessments of 3D CT images. The experimental results showed that our approach, using deep learning for several 2D radial sections from localized 3D breast regions, can predict breast density in non-contrast 3D CT images.

The classification performances for the different categories of breast density varied. We confirmed that our scheme showed a 100% true positive (TP) rate for category 4 (dense breasts containing more than 75% of glandular tissue). The TP rates were 84% and 69% for categories 3 and 4, respectively, which were composed of 25–50% and 50–75% of glandular tissue, respectively. Two CT category 1 cases among the test dataset were misclassified as category 2. Thus, further improvements in the classification of breast density are needed in the future.

In conclusion, we have proposed a novel approach that can automatically classify breast density into four categories in 3D CT images. The proposed scheme has a simple architecture largely based on a deep CNN, and uses a supervised learning approach to reduce the costs of development and increase computational efficiency. The experimental results from 3D CT images showed that our approach could automatically and correctly classify breast densities into four categories in 76% of patient cases. Our proposed scheme demonstrated the potential of deep learning for the prediction of breast cancer risk in 3D CT images acquired for various diagnostic purposes.

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