International Journal of Research in Pharmacy and Pharmaceutical Sciences
www.pharmacyjournal.in
ISSN: 2455-698X
Received: 06-09-2021, Accepted: 23-09-2021, Published: 07-10-2021
Volume 6, Issue 5, 2021, Page No. 7-12

A review on breast cancer pathological image processing

Shubham S Bagade
Sandip Foundation's, Sandip Institute of Pharmaceutical Sciences, Nashik, Maharashtra, India

Abstract
Breast cancer is the most frequent type of cancer. Breast pathological image processing has become an essential tool for the early detection of breast cancer. Using medical image processing to help doctors discover probable breast cancer as early as possible has long been a hot issue in medical image diagnostics. This work systematically elaborates on a breast cancer recognition technique based on image processing from four perspectives: breast cancer detection, picture segmentation, image registration, and image fusion. The achievements and application scope of supervised learning, unsupervised learning, deep learning, CNN, and so on in breast cancer examination is expounded. The prospect of unsupervised learning and transfer learning for breast cancer diagnosis has been prospected. Finally, the privacy protection of breast cancer patients is put forward. The accomplishments and application breadth of supervised learning, unsupervised learning, deep learning, CNN, and other methods in breast cancer examination are discussed. Unsupervised learning and transfer learning have been considered for breast cancer detection. Finally, breast cancer sufferers' private rights are advocated for. Pseudocolor display uses an image as a baseline and superimposes the image's grey and contrast characteristics to be fused with the benchmark image. The tomographic presentation technique may simultaneously show the merged three-dimensional data in cross-sectional, coronal, and sagittal pictures, making it easier for the observer to diagnose. The three-dimensional presentation approach, specifically three-dimensional reconstruction, involves displaying the merged breast data in the form of three-dimensional pictures, which allow for a more intuitive observation of the lesions' spatial anatomical location. The back projection was the first approach to 3D reconstruction. There are two popular reconstruction approaches at the moment: filtered back projection and convolution back projection. Three-dimensional images have a high information capacity, and future three-dimensional image fusion technologies will focus on image fusion research. New image fusion approaches are developing as a result of the advancement of multidisciplinary research. Image fusion research will concentrate on wavelet transform, nonlinear registration based on finite element analysis, and artificial intelligence technologies in breast image fusion.

Keywords: breast cancer, tumor, convolutional neural networks, pcanet, mammography, topology

Introduction

Breast cancer is among the frequent types of cancer. According to a Chinese Women's study, breast cancer is the leading cause of malignant tumors in Chinese women, and the incidence rate is growing year by year. The key to lowering breast cancer mortality is early detection and treatment. Mammography is by far the most widely used technique for detecting breast cancer. The best approach to minimizing breast cancer mortality is early intervention and therapy. Mammography is now the most commonly used technique for detecting breast cancer. However, due to the massive volume of data and the poor imaging characteristics of early breast cancer, early detection is highly challenging.

Image processing of breast pathology, which primarily involves examining masses, calcifications, and breast density, has become an essential means of early diagnosis of breast cancer with the advent of image processing technology and early diagnosis technology. In breast mammography, one of the most common symptoms of breast cancer is bulk. The following are the fundamental processes of pathological image processing: The first step is image preparation, which involves removing background, marker, pectoral muscle, and noise, as well as breast segmentation and picture enhancement. Second, a basic image processing approach is used to locate the region of interest. Then, characteristics that might represent quality are retrieved, such as texture and morphological traits. Finally, the neoplasm and normal tissue were distinguished based on the retrieved factors. A substantial breast density is another indication of breast cancer on X-ray imaging [1]

A range of medical pictures with various imaging methods is the subject of breast pathology image processing. X-ray imaging (X-CT), magnetic resonance imaging (MRI), nuclear medicine imaging (NMI), and ultrasonic imaging (UI) are all familiar sources of medical imaging applied in health centers. X-ray imaging (X-CT) is used to identify cerebral vascular disorders and intracranial bleeding, primarily using X-ray tomography, such as brain tomography [2].

Breast cancer diagnosis based on medical imaging is based on the gathering and analysis of medical images. Image acquisition speed resolution has considerably increased over the years.

On the other hand, image diagnosis is restricted by the doctor's expertise, competence, and other subjective criteria, and its capacity to replicate and promote is limited. The image processing technology is used in medical imaging processing to reduce reliance on clinicians. Lesion detection, image segmentation, image registration, and image fusion are examples of medical image processing. [5, 6].

Detection of Breast Cancer

Breast cancer screening approaches are primarily based on image processing of lesion detection, lesion site matching, and extraction of lesion feature values. Breast cancer detection can use supervised learning or traditional image processing to pinpoint the location of a potential lesion. One of the most effective profound learning instances in recent years is image processing with Convolutional Neural Networks (CNN). In breast cancer image analysis, CNN is used to map the input layer, pool layer, modified linear unit, link layer, and output layer, and forecast the information represented by medical pictures. Setio *et al*., for example, retrieved the characteristics of pulmonary nodules from 9 distinct orientations of 3D chest CT scans, chose the suitable candidate as the center, and categorized the candidates using CNN [3, 11].

Ross *et al*. split the 3D picture into 2D patches and then randomly rotated the 2D patches to obtain the "2.5D" image. The CNN was utilized to detect early cancer characteristics from a 2.5D image. Combining deep learning and image processing enhances lesion detection accuracy, but nondeep learning classifiers such as support vector machines are difficult to attain high accuracy [12]. The accuracy of the CNN algorithm is dependent on expert training of initial markers and requires a wide variety of case coverage. As a result, the promotion of CNN in the field of medical image processing is constrained by resources "transfer learning," which can reduce CNN's reliance on initial marker training to a certain extent, but the application of transfer learning itself is limited, making it challenging to find transfer learning application conditions between medical images of human organs [13, 14].

Tumor markers can help in the early detection of breast cancer. Tumor markers are chemicals that tumor cells make and release during growth and reproduction. When the amount of these chemicals reaches a particular level, they may be recovered from breast pictures. Early feature values can be detected via SIFT (scale-invariant feature transform) or HOG (Histogram of Oriented Gradient), among other methods. Combining image processing technology with reinforcement learning technology can significantly minimize reliance on a human doctor's experience. Two-dimensional slices are processed using image processing technology, and then reinforcement learning is utilized to establish the enhancement target. The best choice strategy is determined by assessing the pathological correctness of each discrete two-dimensional slice to maximize the advantage of deciding the pathological correctness of the entire group of two-dimensional pieces. The segmentation, extraction, three-dimensional reconstruction, and three-dimensional presentation of human breast, surrounding soft tissue, and lesion are accomplished using the analysis and processing of two-dimensional slice images. Following feature calibration, reinforcement learning is utilized to assess the lesion and area around the breast quantitatively. Continual tries do learning out in conjunction with the revenue objective.

The objective is to maximize revenue value. According to the reinforcement learning approach, breast cancer does not need to generate proper breast cancer identification action. Reinforcement learning is based on self-learning, which means that it is continually attempting and making mistakes and constantly recording the maximum value of revenue in a trial-and-error process until the technique of determining the total value of income is discovered [8, 9].

Breast Cancer Image Segmentation

The medical image segmentation examines the similarity of feature elements between pictures and separates the image into multiple sections based on the provided feature variables. Cells, tissues, and organs are the most common objects in medical picture segmentation. The region-based segmentation approach primarily depends on the image's spatial local attributes, such as grayscale, texture, and other pixel statistical properties. The boundary-based segmentation approach primarily uses gradient information to identify the target's border. For example, the rapid marching algorithm and the watered transform medical image segmentation technique can segment the picture quickly and correctly [15].

Image segmentation technology has advanced significantly in recent years, owing to the growth of other developing areas, and new approaches developed through interdisciplinary research have emerged indefinitely. Some novel picture segmentation approaches for breast cancer diagnosis have been developed, including the statistical method, the fuzzy theory method, the neural network method, the wavelet analysis method, the model-based snake model (dynamic contour model), and the combination optimization model. Even though new segmentation approaches have been developed, the results are not perfect. At the moment, the research focuses on a knowledge-based segmentation method. Some prior knowledge is introduced into the segmentation process via some means to constrain the computer segmentation process, allowing the segmentation results to be controlled within a range we can understand without going too far [16]. For example, if the grey value of a tumor in the liver differs significantly from that of the normal liver, the tumor and the normal liver will not be treated as different tissues. The approaches mentioned above have their own set of restrictions. The outcomes are satisfactory in certain circumstances but not ideal in others. Human involvement is also demanded [17]. Medical image segmentation differs significantly from image segmentation in other disciplines. The current classical algorithms' performance in medical picture segmentation is poor. It is still required to research to improve picture segmentation's accuracy, speed, flexibility, and robustness [18]. The image segmentation approach based on previous knowledge may effectively regulate the picture segmentation border. In the segmentation of intrahepatic mass, for example, the image segmentation technique based on prior knowledge can distinguish the intrahepatic group and normal liver by grey value. Image segmentation based on previous knowledge, on the other hand, necessitates a considerable amount of past data. The more past data there is, the more accurate the results will be. Ghesu *et al*., for example, employed deep learning and edge space learning to recognize and segment cardiac ultrasound pictures using 2891 times of cardiac ultrasound data [17, 18]. Exploration of parameter space and data sparsity are significant aspects in improving the efficiency of medical picture segmentation. Brosch *et al*. developed a 3D deep convolution coder network to separate multiple sclerosis brain lesions and usual brain areas using convolution and deconvolution [19]. In brain tumor segmentation research, data normalization and data enhancement algorithms improve picture enhancement and core areas of suspected tumors, and good results are obtained [20]. The study of medical image segmentation methods reveals the following notable characteristics: it is difficult for any single existing image segmentation algorithm to achieve satisfactory results for general images, so more emphasis should be paid to the effective combination of multiple segmentation algorithms. Because of the complexity of human anatomical structure and the systematicity of function, although studies on automatic segmentation of medical images to distinguish the required organs and tissues or find the lesion area has been conducted, the existing software packages generally cannot complete the automatic segmentation. Manual intervention of anatomy is still required [21]. Because a computer cannot now accomplish picture segmentation, the human-computer interactive segmentation technique has progressively been the focus of study. The development of innovative segmentation techniques is primarily focused on characteristics that are automated, accurate, quick, adaptable, and resilient. The future development direction of medical image segmentation technology is the full use of classical segmentation technology and current segmentation technology [22, 23].

Breast Cancer Image Registration

The first mock exam of image fusion is image registration. Multiple modalities or types of picture registration and fusion are required in breast cancer clinical diagnosis. More information can assist doctors in providing more accurate diagnoses [24]. In the clinical diagnosis of breast cancer, medical image registration primarily locates reference points in two or more pictures; the reference point is identified in a coordinate system by spatial location transformation, such as rotation. Registration necessitates one-to-one correspondence of points across pictures; that is, each point in one image space has analogous points in another image space, or in the context of medical diagnosis, the points in the image may be properly or roughly precisely matched [25–27]. There are two forms of registration: those based on external features and those based on internal features. Registration based on internal visual characteristics is non-invasive and traceable, which is the focus of registration algorithm research [28].

There are two primary types of medical registration research for breast cancer: the first uses a deep learning network to evaluate the similarity of two pictures and drive iterative optimization. The second uses a depth regression network to predict the conversion parameters directly. The former utilizes deep learning to measure similarity and still requires the standard registration technique for iterative optimization. It does not fully use the benefits of deep learning, it takes a long time, and it is not easy to accomplish real-time registration. As a result, only the latter is investigated and described, and the conclusion is restricted to this type of nonrigid registration technique. There are two approaches to get tags based on supervised learning: the standard classical registration technique is utilized for registration, and the deformation field is utilized as tags. The second step is to mimic the original picture as a stationary image, the distorted picture as a moving image, and the simulated distortion field as a label. The registration pair is sent into the network to produce the deformation field, and the moving image is interpolated to obtain the registration image using unsupervised learning. It is comparable to the 3D image. The 3D picture is fed into the network to generate the deformation field (dx, dy, dz), and then interpolation is used to obtain the registration image. However, the registration of medical images of breast cancer remains an unsolved classic challenge. In this sector, there is no widely acknowledged gold standard and no big matching database. Deep learning algorithms have shown some success in breast cancer image registration. There are several reasons for this: the expert knowledge of the field is well utilized, the data are properly pre-processed and analyzed by data augmentation, a particularly unique network structure is designed for a specific task, and the appropriate super parametric optimization method is used, such as parameter adjustment based on instinct or the Bayesian method.

Multimodality medical image registration, such as nonrigid multimodal medical image registration based on PCANet structure representation [29], is a novel trend in breast cancer registration.

PCANet can learn intrinsic features from a large number of medical pictures automatically using multilayer linear and nonlinear transformation, which has higher information entropy than the artificial feature extraction technique. Multilevel image characteristics derived from each layer of PCANet may represent multimodal pictures well. The combination of medical image registration technology and informatics theory provides a new avenue for breast cancer image registration. The idea of maximal information entropy, for example, is used to picture registration, which may increase the variety of information while retaining the essential information while ignoring the secondary information. A novel trend in medical picture registration is three-dimensional multimode image registration [30-35]. It contains more information than a two-dimensional picture and can better assist a doctor's diagnosis. Furthermore, feature points are collected from existing breast cancer pictures using specific novel image registration methods, such as image identification of breast cancer based on topology. They are integrated with a matching region with a particular topological structure serving as the matching template. Regions with comparable topological patterns are discovered in the breast pictures; these regions may represent breast cancer. The following are the critical processes in picture detection of breast cancer based on topology: the first is to extract feature points or feature areas of a specified scale and combine them into topological templates.

The topology of the to-be-matched picture is retrieved. Regions with similar topology are discovered by comparing the topology of the picture to be matched with the topology template.

The similarity of alike topology and feature points in a topology template is compared, and the product of topology and feature point similarity is considered the final similarity. Figure 1 shows a schematic design of picture recognition based on topological structure. Figure 1 shows the topology template on the left, the topology retrieved from the picture to be matched on the middle, and the region with the comparable topology on the right [36].

Other approaches, such as wavelet transform algorithms, statistical parametric mapping algorithms, and evolutionary algorithms, are being continually integrated into breast cancer picture registration. The future development path of medical image registration is the integration of multi-objective optimization, reinforcement learning, and other approaches with medical image registration.

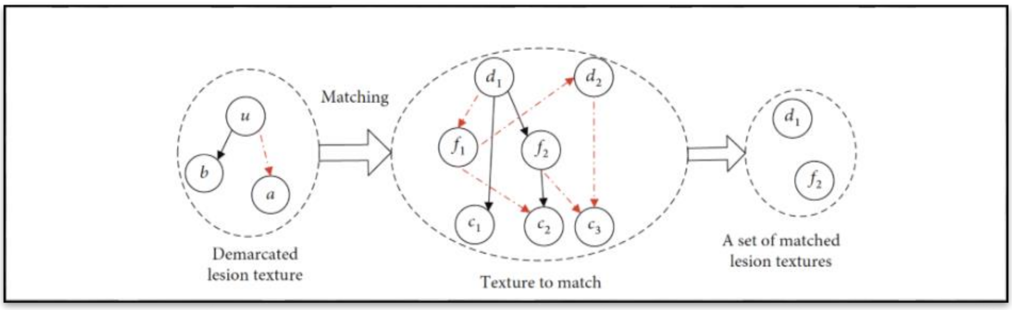

Fig 1: Image recognition sketch based on topological structure.

Breast Cancer Image Fusion

Breast cancer picture fusion collects relevant information from numerous images, filters redundant data, and increases image medical value. From low to high image fusion, there is signal level fusion, data-level fusion, feature level fusion, and decision level fusion.

1. Signal level

The unprocessed sensor data is combined in the signal domain to generate a fused signal at the most basic level. The fused signal has the same shape as the source signal, but it is of higher quality. The sensor signal can be represented as a random variable mixed with various associated sounds. In this instance, fusion may be regarded as an estimating process, and signal level picture fusion is, to a significant degree, the optimal concentration or distribution detection problem of signal, requiring the highest registration in time and space.

2. Pixel level

The pixel-level image fusion is the most fundamental of the three stages. After pixel-level picture fusion, the resulting image has additional detailed information, such as edge and texture extraction, useful for further image analysis, processing, and comprehension. It may also reveal the possible target, which aids in assessing and recognizing the potential target pixels. This approach can conserve as much information from the source picture as feasible while increasing the richness and features of the fused image [37]. This benefit is unique and only available in pixel-level fusion. However, the limits of pixel-level picture fusion cannot be overlooked. Because it operates on pixels, the computer must analyze a significant amount of data, and the processing time is very long, so the fused image cannot be presented in time, and real-time processing is not possible. Furthermore, the volume of information in data transfer is enormous, and it is quickly impacted by noise. Furthermore, if you directly participate in picture fusion without rigorous image registration, the fused image will be blurred, and the target and details will be illegible and inaccurate.

3. Feature level

The goal of feature-level image fusion is to extract feature information from a source picture. The feature information in the source image is information on the target or region of interest, such as an edge, person, structure, or vehicle. The feature information is then examined, processed, and combined to produce the fused picture features. Target identification based on fused features outperforms the original image in terms of accuracy. The picture data is compressed via feature-level fusion before being examined and processed by a computer. Memory and time used will be decreased when compared to the pixel level, and the real-time performance of the necessary image will be enhanced. Feature-level image fusion needs less image matching precision than the first layer and has a higher processing performance. However, because it extracts picture characteristics as fusion information, it will lose a significant amount of detailed information.

4. Picture Fusion

Picture fusion at the decision level is a cognitive-based approach that is not only the highest degree of image fusion but also the highest level of abstraction. Image fusion at the decision level is being pursued [38]. The feature information received from the feature level picture is employed according to the particular needs of the problem, and then the optimal choice is produced directly based on certain criteria and the credibility of each conclusion, that is, the likelihood of the target's presence. The computation of decision level image fusion is the shortest of the three fusion levels, however this technique is heavily dependent on the previous level, and the picture is not as clear as the previous two fusion methods. The decision level image fusion is difficult to accomplish, yet noise has the least impact on picture transmission.

To summarise, data-level fusion is the process of immediately processing gathered data to produce the fused image, which serves as the foundation for high-level image fusion. The information included in distinct pictures is preserved through feature-level fusion. The greatest degree of picture fusion is decision-level fusion, which is based on subjective requirements. Data level fusion is the primary approach used in breast medical picture fusion. Multimodality medical image fusion, for example, is a technique that combines information from many dimensions. It has the potential to give more complete and reliable data for the clinical identification of breast cancer [39]. Image fusion is separated into two steps: image data fusion and fusion image presentation. At the moment, breast image data fusion is primarily dependent on pixels, which process the picture point by point and total the grey levels of the corresponding pixels in the two photographs. However, the image will be blurred to some amount as a result of employing this approach. The fusion technique based on breast image characteristics must extract image features and perform target segmentation and other image processing. Fusion picture display options include pseudocolor, tomographic, and three-dimensional displays.

Conclusion

Deep learning and reinforcement learning are close combinations of machine learning algorithms and breast cancer image processing that have achieved significant progress. Breast cancer image processing differs significantly from other noise reduction, grayscale transformation, target segmentation, and feature extraction. The standard image processing approach is not directly applicable to the processing of breast cancer images. Deep learning accumulation in image processing cannot be immediately applied to breast cancer image processing. Reinforcement learning is a category of unsupervised learning, as opposed to deep learning. It employs an incentive mechanism that does not need a considerable sample space. When compared to deep learning, reinforcement learning offers a broader application and a cheaper cost of promotion. Furthermore, reinforcement learning has produced excellent results in chess, man-machine games, and other suited disciplines for sophisticated logic processing. Integrating reinforcement learning and medical image processing will play a more prominent role in breast cancer clinical diagnosis and prediction.

Acknowledgmemts
I would like to extend my special thanks to Sandip Institute of Pharmaceutical Sciences. The assistance provided by Dr. Laxmikant Borse, Dr. Atul Bendale and Dr. Anil Jadhav is really appreciated.

References
1. Elston CW, Ellis IO, Pinder SE, "Pathological prognostic factors in breast cancer," Critical Reviews in Oncology/-Hematology,1999:31(3):209-223,.
2. Udupa JK, Herman GT. "Medical image reconstruction, processing, visualization, and analysis: the MIPG perspective," IEEE Transactions on Medical Imaging, 2002:21(4):281-295.
3. Roth HR, Lu L, Liu J *et al*. "Improving computer-aided detection using convolutional neural networks and random view aggregation," IEEE Transactions on Medical Imaging,2016:35(5):1170-1181.
4. Cserni G, Amendoeira N, Apostolikas *et al*. "Pathological work-up of sentinel lymph nodes in breast cancer. Review of current data to be considered for the formulation of guidelines," European Journal of Cancer,2003:39(12):1654-1667.
5. Hou Y. "Breast cancer pathological image classification based on deep learning," Journal of X-Ray Science and Technology,vol,2020:28(4):727-738.
6. Wu SG, Wang J, Lei J *et al*. "Prognostic validation and therapeutic decision-making of the AJCC eighth pathological prognostic staging for T3N0 breast cancer after mastectomy," Clinical and Translational Medicine,2020:10(1):125-136.
7. Mcinerney T, Terzopoulos D. "Deformable models in medical image analysis: a survey," Medical Image Analysis,1996:1(2):91-108.
8. Litjens G, Kooi T, Bejnordi BE *et al*. "A survey on deep learning in medical image analysis," Medical Image Analysis,2017:42:60-88.
9. TMD. (ne Lehmann), Handels H, KHMH. (ne Fritzsche) *et al*., "Viewpoints on medical image processing: from science to application," Current Medical Imaging Reviews,2013:9(2):79-88.
10. Setio F, Ciompi G, Litjens *et al*. "Pulmonary nodule detection in CT Images: False Positive Reduction using Multi-View convolutional networks," Medical Imaging,2016:35(5):1160-1169.
11. Guo Z, Liu H, Ni H *et al*. "Publisher correction: a fast and refined cancer regions segmentation framework in wholeslide breast pathological images," Scientific Reports,2020:10(1):8591.
12. Roth HR, Lu L, Seff A. *et al*. "A new 2.5D representation for lymph node detection using random sets of deep convolutional neural network observations," in Medical Image Computing and Computer-Assisted Intervention – MICCAI, 2014. MICCAI 2014, P. Golland, N. Hata, C. Barillot, J. Hornegger, and R. Howe, Eds., vol. of Lecture Notes in Computer Science, pp. Springer, Cham,2014:8673:520-527.
13. Moeskops P, Viergever MA, Mendrik AM, de Vries LS, Benders MJNL, Isgum I. "Automatic segmentation of MR brain images with a convolutional neural network," IEEE Transactions on Medical Imaging,2016:35(5):1252-1261.
14. Pham, Xu C, Prince JL. "Current methods in medical image segmentation," Annual Review of Biomedical Engineering,2000:2:1:315-337.
15. Lehmann TM, Gonner C, Spitzer K. "Survey: interpolation methods in medical image processing," IEEE Transactions on Medical Imaging,1999:18(11):1049-1075.
16. Cootes TF, Taylor CJ. "Statistical models of appearance for medical image analysis and computer vision," Proceedings of SPIE - The International Society for Optical Engineering,2001:4322:1.
17. Ghesu FC, Georgescu B, Mansi T, Neumann D, Hornegger J, Comaniciu D. "An artificial agent for anatomical landmark detection in medical images," in Medical Image Computing and Computer-Assisted Intervention - MICCAI 2016. MICCAI 2016, S. Ourselin, L. Joskowicz, M. Sabuncu, G. Unal, and W. Wells, Eds., vol. 9902 of Lecture Notes in Computer Science, Springer, Cham, 2016.
18. Ghesu FC, Krubasik E, Georgescu B *et al*. "Marginal space deep learning: efficient architecture for volumetric image parsing," IEEE Transactions on Medical Imaging,2016:35:5:1217-1228.
19. Brosch T, Tang LYW, Yoo Y, Li DKBA. Traboulsee, and R. Tam, "Deep 3D convolutional encoder networks with shortcuts for multiscale feature integration applied to multiple sclerosis lesion segmentation," Medical Imaging,2016:35(5):1229-1239.
20. Wahab N, Khan A, Lee YS. "Transfer learning based deep CNN for segmentation and detection of mitoses in breast cancer histopathological images," Microscopy,2019:68(3):216-233.
21. Sohail, Mukhtar MA, Khan A, Zafar MM, Zameer A, Khan S. "Deep Object Detection Based Mitosis Analysis in Breast Cancer Histopathological Images,", 2020. http://arxiv.org/abs/2003.08803.
22. Milletari F, Navab N, Ahmadi SA. "V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation," 2016 Fourth International Conference on 3D Vision (3DV) Stanford, CA, USA, 2016, 2016, 565-571.
23. Ishihara S, Ishihara K, Nagamachi M, Matsubara Y. "An analysis of Kansei structure on shoes using self-organizing neural networks," International Journal of

Industrial Ergonomics,1997:19(2):93-104.
24. Maintz JB, Viergever MA. “A survey of medical image registration,” Computer & Digital Engineering,2009:33(1):140-144.
25. Hill DLG, Batchelor PG, Holden M, Hawkes DJ. “Medical image registration,” Physics in Medicine & Biology,2008:31(4):1-45.
26. Greenspan H, van Ginneken B, Summers RM. “Guest editorial deep learning in medical imaging: overview and future promise of an exciting new technique,” IEEE Transactions on Medical Imaging,2016:35(5):1153-1159.
27. Kamnitsas K, Ledig C, Newcombe VFJ *et al*. “Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation,” Medical Image Analysis,2016;36:61.
28. Tajbakhsh N, Shin JY, Gurudu SR *et al*. “Convolutional neural networks for medical image analysis: full training or fine tuning,” IEEE Transactions on Medical Imaging,2016:35(5):1299-1312.
29. Anthimopoulos M, Christodoulidis S, Ebner L, Christe A, Mougiakakou S. “Lung pattern classification for interstitial lung diseases using a deep convolutional neural network,” IEEE Transactions on Medical Imaging,2016:35(5):1207-1216.
30. Hoo-Chang Shin MR, Orton DJ, Collins SJ, Doran MO, Leach. “Stacked autoencoders for unsupervised feature learning and multiple organ detection in a pilot study using 4D patient data,” IEEE Transactions on Pattern Analysis and Machine Intelligence,2013:35(8):1930-1943.
31. Sahiner B, Heang-Ping Chan N, Petrick *et al*. “Classification of mass and normal breast tissue: a convolution neural network classifier with spatial domain and texture images,” IEEE Transactions on Medical Imaging,1996:15(5):598-610.
32. Nie D, Wang L, Gao Y, Shen D. “Fully convolutional networks for multi-modality isointense infant brain image segmentation,” in 2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI). Prague, Czech Republic, 2016, 1342-1345.
33. Roth HR, Lu L, Farag A. *et al*. “DeepOrgan: multi-level deep convolutional networks for automated pancreas segmentation,” in Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015, N. Navab, J. Hornegger, W. Wells, and A. Frangi, Eds., of Lecture Notes in Computer Science, Springer, Cham,2015:9349:556-564.
34. Wang D, Khosla A, Gargeya R, Irshad H, Beck AH. “Deep Learning for Identifying Metastatic Breast Cancer,”, 2016. http://arxiv.org/abs/1606.05718.
35. Li R, Zhang W, Suk H I *et al*., “Deep learning based imaging data completion for improved brain disease diagnosis,” in Medical Image Computing and Computer-Assisted Intervention– MICCAI 2014, vol. 8675 of Lecture Notes in Computer Science, Springer, Cham, 2014, 305-312.
36. Ya Nan Z, Ming Cheng Q, Yu Peng L. “Recommendation method based on social topology for cold-start users,” Journal of Zhejiang University (Engineering Science),2016:50:1001-1008.
37. Bar Y, Diamant I, Wolf L, Greenspan H. “Deep learning with non-medical training used for chest pathology identification,” in Medical Imaging 2015: Computer-Aided Diagnosis, International Society for Optics and Photonics, 2015.
38. Kooi T, Litjens G, van Ginneken B *et al*., “Large scale deep learning for computer aided detection of mammographic lesions,” Medical Image Analysis,2017:35:303-312.
39. Yu C, Chen H, Li Y, Peng Y, Li J, Yang F. “Breast cancer classification in pathological images based on hybrid features,” Multimedia Tools and Applications,2019:78:15:21325-21345.