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Advancements in Research on the Classification of Benign and Malignant Breast Tumors Utilizing Ultrasound Radiomics and Deep Learning

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Abstract: This paper examines the applications of traditional machine learning and deep learning in the analysis of breast ultrasound images for tumor diagnosis and explores recent developments in multimodal imaging. Traditional machine learning efficiently classifies breast ultrasound images through preprocessing, feature extraction, and selection, utilizing classifiers such as support vector machines. However, the design of features is highly dependent and its application scope is limited. Deep learning methods, particularly convolutional neural networks, autonomously extract sophisticated features, demonstrating enhanced classification performance and generalization capabilities. For instance, they achieve diagnostic accuracies exceeding 90% in large-scale datasets, with some studies outperforming clinicians. Moreover, this study highlights that the multimodal analysis strategy, integrating breast ultrasound with shear wave elastography, compensates for the limitations of unimodal images and enhances diagnostic accuracy and reliability, signifying a significant advancement in the technology for early breast cancer diagnosis.

Keywords: Breast Ultrasound Imaging; Conventional Machine Learning; Deep Learning; Multimodal Diagnosis.

1. Introduction

Breast cancer is a malignant tumor that develops in breast tissue. This disease is influenced by various carcinogenic factors, including genetics and environmental components. It occurs when breast epithelial cells grow abnormally and proliferate more rapidly than healthy cells, leading to the formation of lumps [1]. Breast cancer is the most prevalent cancer among women worldwide and is the primary cause of cancer-related deaths in this group. In 2020, the International Agency for Research on Cancer (IARC) released global cancer statistics, indicating that breast cancer had overtaken lung cancer as the most diagnosed cancer globally [2, 3]. In that year, approximately 9.23 million women were diagnosed with cancer worldwide, with about 2.26 million cases (24.5% of new cases in women) being breast cancer. Furthermore, there were about 4.4 million new cancer-related deaths among women worldwide, with approximately 685,000 deaths due to breast cancer (15.5% of new cancer deaths in women) [4]. By 2040, the IARC projects that the incidence of breast cancer will increase by more than one-third, exceeding 3 million new cases annually, and the mortality rate will rise by more than half, resulting in over 1 million deaths per year [5].

2. Application of Different Techniques in Breast Diagnosis

2.1. Applications of Mammography and Magnetic Resonance Imaging

Early screening and treatment are crucial for patients with breast cancer, significantly enhancing survival rates, reducing the need for postoperative adjuvant therapy, and improving quality of life [6, 7]. Common clinical imaging modalities include mammography [3, 4], magnetic resonance imaging (MRI) [8, 9], and breast ultrasound [10, 11], each offering distinct advantages and applications. Mammography is a straightforward, relatively cost-effective method with high imaging resolution. It is particularly sensitive to intramammary calcifications, capable of detecting calcified foci smaller than 2 mm [12, 13]. However, mammography has limitations, particularly a low detection rate for dense breast lesions due to glandular folding in X-rays, which can obscure tumors and reduce contrast. Studies indicate that even under optimal photographic and diagnostic conditions, the sensitivity of mammography in detecting breast cancer ranges only between 85% to 90%, leaving 10% to 15% of breast cancers undetected due to insufficient contrast in dense breasts, small tumors, specific tumor subtypes, and other factors [14]. Mammography involves some radiation exposure and is primarily recommended for women over 40 years old; it also requires breast compression, which can be painful. In contrast, MRI offers excellent soft-tissue resolution, operates without radiation, and is highly sensitive for detecting breast lesions, particularly in dense breasts [15]. Three-dimensional MRI imaging facilitates precise lesion localization and intuitive visualization, which is beneficial for pre-surgical assessments and breast reconstruction surgeries. Unlike mammography, MRI does not require breast compression and generally causes minimal discomfort [16]. However, MRI is time-intensive and costly; it is less effective than mammography in displaying calcifications, necessitating its combination with mammography when needed; it requires intravenous contrast medium injection, which carries the risk of adverse reactions. Additionally, MRI is unsuitable for patients with claustrophobia due to the enclosed examination space, prolonged examination duration, and significant noise, which may induce psychological discomfort [17].

2.2. Application of Ultrasound in Breast Diagnosis

Breast ultrasonography employs ultrasound waves that propagate through the body, processing the echo signals to generate a sonogram [18]. The sonogram displays the size, shape, contour boundaries, echo type, internal echo condition, and posterior attenuation of the lesion, aiding in the determination of the lesion's nature. Ultrasound technology for breast cancer diagnosis dates back to the 1950s, initiated by Wild et al. [19, 20]. In 1972, Kossoff G. documented a case demonstrating clear visualization of the breast and its pathological features using gray-scale ultrasound. Since then, breast ultrasound has progressed to include color Doppler ultrasound and shear wave elastography. Breast ultrasound imaging is non-invasive, involves no radiation, and can be performed repeatedly. It offers real-time advantages and allows dynamic observation of lesion elasticity, activity, and color Doppler flow [21, 22]. It is suitable for women of all ages and during all physiological stages, including pregnancy and lactation. Breast ultrasound provides excellent soft-tissue resolution and can clearly visualize the breast structure and all chest wall layers, especially in dense breasts, where it can detect small masses down to the millimeter level [23]. However, ultrasound imaging is often hampered by substantial noise and artifacts, low resolution, and low contrast, which can degrade image quality. Moreover, the imaging styles can vary significantly among different ultrasound equipment manufacturers, requiring operators to possess skilled techniques and substantial experience to achieve high-quality imaging [24]. Additionally, manual diagnosis from ultrasound images heavily depends on the clinician's personal experience, introducing subjectivity and potentially large variances in diagnostic outcomes [25].

3. Ultrasound Conventional Machine Learning and Deep Learning for Breast Tumor Diagnosis

To address these challenges, early researchers developed a computer-aided diagnosis system (CAD) [26, 27]. This system enhances the accuracy of ultrasound image interpretation by automating the analysis process, thereby saving time and reducing labor costs. The system is capable of fully automating tasks such as lesion area segmentation and classification of tumors as benign or malignant, assisting physicians in the diagnostic process. Breast ultrasound image classification techniques are primarily divided into two categories: traditional machine learning and deep learning [28].

3.1. Ultrasound Conventional Machine Learning in Breast Tumor Diagnosis

Traditional machine learning methods for breast ultrasound image classification typically involve the following steps: initially, preprocessing operations are conducted to mitigate issues like speckle noise in breast ultrasound images. Techniques such as denoising and enhancement are crucial to improve the images' contrast and resolution. This is followed by feature extraction, where texture, morphology, and other characteristics of the region of interest are derived from the original image to represent tumor attributes. This provides a quantitative foundation for subsequent benign and malignant classifications. Next, feature selection is performed to identify significant features essential for classification, eliminate redundant features, and prevent model overfitting, which also helps in accelerating the classification algorithm. Finally, the selected features are classified and identified using common classifiers such as support vector machines [29], K-nearest neighbors, decision trees, and random forests.

For example, Mohamed et al. [30] utilized a random forest classifier to categorize 59 breast ultrasound (BUS) images. They first transformed the original low-resolution images into high-resolution images using a super-resolution algorithm, followed by the extraction of regions of interest and features including gray scale covariance matrix, local binary pattern features, gradient direction histogram, and phase-consistent local binary pattern features, and subsequently performed classification. Similarly, Liu et al. [31] classified 87 BUS images using a support vector machine. They began by enhancing images with a multi-peak generalized histogram equalization method, then extracted features such as gray dependency matrix, gradient direction histogram, and fractal features, used stepwise regression for feature selection, and finally applied a support vector machine for classification. Additionally, Kriti et al. [32] explored the impact of different speckle filters on the classification of BUS images in a study involving 100 BUS images.

The experimental results revealed that the integration of texture features from the original image with morphological features from the image post-speckle noise reduction, using the Detail Preserving Anisotropic Diffusion (DPAD) filtering algorithm [33-35], was most effective in the differential diagnosis of benign and malignant tumors in breast ultrasound (BUS) images, achieving a classification accuracy of 96%. Specifically, the DPAD algorithm was applied to remove speckle noise from the original image to produce a denoised image. Subsequently, the active contour model was employed to segment the tumor region in both the original and denoised images. Following this, 149 texture features were extracted from the segmented original image and 13 morphological features from the segmented denoised image. Principal Component Analysis (PCA) was then utilized for feature analysis and selection, with Support Vector Machine (SVM) employed for classification [36]. While traditional machine learning classification models can aid clinicians in diagnosis and enhance the accuracy of classifying benign and malignant tumors, these models require the manual design of features prior to classification. This necessitates extensive medical domain knowledge and tailored manual features for different datasets, which can limit the models' applicability [37]. In conclusion, traditional machine learning methods for breast ultrasound image classification exhibit certain limitations [38].

3.2. Deep Learning in Breast Tumor Diagnosis Using Ultrasound

Deep learning methods enable the automatic extraction of image features without human intervention, significantly advancing the classification of breast ultrasound images [39]. Deep learning models exhibit superior learning and generalization capabilities compared to traditional machine learning models. They can more comprehensively and accurately extract features from the image tumor region, addressing the issue of incompleteness associated with manually designed features, and can achieve higher classification accuracy [40]. These advantages have made deep learning a prevalent choice in the field of breast ultrasound image classification [41]. For instance, Antropova et al. [42] analyzed a dataset of 2393 regions of interest (ROIs) from 1125 cases using convolutional neural networks (CNNs). They demonstrated that features automatically extracted by CNNs outperformed manually designed features in classifying breast ultrasound images. Similarly, Han et al. [43] employed GoogLeNet to classify 7408 BUS images from 5151 patient cases. The image ROIs were manually cropped by an imaging physician, and the dataset was augmented to 960,000 images using data enhancement techniques. The final model achieved an accuracy of 90%, a sensitivity of 0.86, a specificity of 0.96, and an area under the curve (AUC) exceeding 0.9. Furthermore, Fujioka et al. [44] utilized DenseNet169 to classify the benign and malignant nature of breast tumors in 304 shear wave elastography (SWE) images. The model demonstrated a sensitivity of 0.857, a specificity of 0.789, and an AUC of 0.898. The diagnostic performance of this model surpassed that of radiologists, highlighting the potential of deep learning in enhancing diagnostic accuracy in breast tumor assessments.

3.3. Application of Multimodality in Breast Tumor Diagnosis

The aforementioned classification experiments using deep learning methods have primarily focused on single-modality breast ultrasound images. While single-modality ultrasound can offer valuable insights, it has inherent limitations. For example, breast ultrasound (BUS) images, with their 256 grayscale levels, provide high resolution that enhances the visibility of tumor boundaries, aiding the model in tumor localization [45]. However, these images are prone to significant speckle noise interference, which can reduce the accuracy of model classifications. Shear wave elastography (SWE) images of breast tumors, on the other hand, leverage the structural and elastic properties of breast tissues, which change in response to pathological alterations, affecting tissue stiffness. The elasticity variations between normal tissue, benign tumors, and malignant tumors are distinct [46-48]. In SWE images, benign tumors typically appear blue due to their soft and homogeneous elasticity, whereas malignant tumors, being hard and heterogeneous in elasticity, present in mixed colors with red foci [49]. Despite providing critical information on tissue elasticity unavailable in BUS images, SWE images suffer from low resolution and unclear tumor boundaries, which can compromise classification accuracy [50, 51]. To overcome these issues, researchers have proposed the use of multimodal breast ultrasound image classification. This approach utilizes images from multiple ultrasound modalities as inputs to enhance tumor classification accuracy. For instance, Qian et al. [52] used B-mode, elastic, and Doppler images from both transverse and longitudinal scans as inputs. They trained a model with 10,815 multimodal breast ultrasound images from 634 patients and tested it on 912 images from 141 patients. The resulting experiment achieved an area under the curve (AUC) of 0.922, indicating that the model's predictive accuracy is comparable to that of an experienced radiologist.

4. Conclusion

In summary, both traditional machine learning and deep learning methodologies have proven to be effective tools for assisting physicians in clinical diagnosis and enhancing the accuracy of breast tumor classification. These technologies not only streamline diagnostic processes but also improve outcomes by enabling more precise and early detection of breast cancers.

References

[1] COUGHLIN S S. Epidemiology of Breast Cancer in Women [J]. Advances in experimental medicine and biology, 2019, 1152: 9-29.

[2] BRAY F, FERLAY J, SOERJOMATARAM I, et al. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries [J]. CA: a cancer journal for clinicians, 2018, 68(6): 394-424.

[3] ZHANG Y N, XIA K R, LI C Y, et al. Review of Breast Cancer Pathologigcal Image Processing [J]. BioMed research international, 2021, 2021: 1994764.

[4] HARBECK N, GNANT M. Breast cancer [J]. Lancet (London, England), 2017, 389(10074): 1134-50.

[5] BARZAMAN K, KARAMI J, ZAREI Z, et al. Breast cancer: Biology, biomarkers, and treatments [J]. International immunopharmacology, 2020, 84: 106535.

[6] CHAPMAN C, MURRAY A, CHAKRABARTI J, et al. Autoantibodies in breast cancer: their use as an aid to early diagnosis [J]. Annals of oncology: official journal of the European Society for Medical Oncology, 2007, 18(5): 868-73.

[7] FAN L, STRASSER-WEIPPL K, LI J J, et al. Breast cancer in China [J]. The Lancet Oncology, 2014, 15(7): e279-89.

[8] OREL S G, SCHNALL M D. MR imaging of the breast for the detection, diagnosis, and staging of breast cancer [J]. Radiology, 2001, 220(1): 13-30.

[9] YU Y, HE Z, OUYANG J, et al. Magnetic resonance imaging radiomics predicts preoperative axillary lymph node metastasis to support surgical decisions and is associated with tumor microenvironment in invasive breast cancer: A machine learning, multicenter study [J]. EBioMedicine, 2021, 69: 103460.

[10] COSTANTINI M, BELLI P, IERARDI C, et al. Solid breast mass characterisation: use of the sonographic BI-RADS classification [J]. La Radiologia medica, 2007, 112(6): 877-94.

[11] DORLING L, CARVALHO S, ALLEN J, et al. Breast Cancer Risk Genes - Association Analysis in More than 113,000 Women [J]. The New England journal of medicine, 2021, 384(5): 428-39.

[12] CONTI A, DUGGENTO A, INDOVINA I, et al. Radiomics in breast cancer classification and prediction [J]. Seminars in cancer biology, 2021, 72: 238-50.

[13] HECK L, HERZEN J. Recent advances in X-ray imaging of breast tissue: From two- to three-dimensional imaging [J]. Physica medica : PM : an international journal devoted to the applications of physics to medicine and biology : official journal of the Italian Association of Biomedical Physics (AIFB), 2020, 79: 69-79.

[14] BIRD R E, WALLACE T W, YANKASKAS B C. Analysis of cancers missed at screening mammography [J]. Radiology, 1992, 184(3): 613-7.

[15] DI MARIA S, VEDANTHAM S, VAZ P. X-ray dosimetry in breast cancer screening: 2D and 3D mammography [J]. European journal of radiology, 2022, 151: 110278.

[16] YU Y, TAN Y, XIE C, et al. Development and Validation of a Preoperative Magnetic Resonance Imaging Radiomics-Based Signature to Predict Axillary Lymph Node Metastasis and Disease-Free Survival in Patients With Early-Stage Breast Cancer [J]. JAMA network open, 2020, 3(12): e2028086.

[17] ALONSO ROCA S, DELGADO LAGUNA A B, ARANTZETA LEXARRETA J, et al. Screening in patients with increased risk of breast cancer (part 1): pros and cons of MRI screening [J]. Radiologia, 2020, 62(4): 252-65.

[18] SOOD R, ROSITCH A F, SHAKOOR D, et al. Ultrasound for Breast Cancer Detection Globally: A Systematic Review and Meta-Analysis [J]. Journal of global oncology, 2019, 5: 1-17.

[19] BITENCOURT A, DAIMIEL NARANJO I, LO GULLO R, et al. AI-enhanced breast imaging: Where are we and where are we heading? [J]. European journal of radiology, 2021, 142: 109882.

[20] KRATKIEWICZ K, PATTYN A, ALIJABBARI N, et al. Ultrasound and Photoacoustic Imaging of Breast Cancer: Clinical Systems, Challenges, and Future Outlook [J]. Journal of clinical medicine, 2022, 11(5).

[21] LE E P V, WANG Y, HUANG Y, et al. Artificial intelligence in breast imaging [J]. Clinical radiology, 2019, 74(5): 357-66.

[22] LANE N, LAHHAM S, JOSEPH L, et al. Ultrasound in medical education: listening to the echoes of the past to shape a vision for the future [J]. European journal of trauma and emergency surgery : official publication of the European Trauma Society, 2015, 41(5): 461-7.

[23] RAHMAN W T, HELVIE M A. Breast cancer screening in average and high-risk women [J]. Best practice & research Clinical obstetrics & gynaecology, 2022, 83: 3-14.

[24] XUE S, ZHAO Q, TAI M, et al. Correlation between Breast Ultrasound Microcalcification and the Prognosis of Breast Cancer [J]. Journal of healthcare engineering, 2021, 2021: 6835963.

[25] YAO Z, LUO T, DONG Y, et al. Virtual elastography ultrasound via generative adversarial network for breast cancer diagnosis [J]. Nature communications, 2023, 14(1): 788.

[26] YOON W B, OH J E, CHAE E Y, et al. Automatic Detection of Pectoral Muscle Region for Computer-Aided Diagnosis Using MIAS Mammograms [J]. BioMed research international, 2016, 2016: 5967580.

[27] CAHAN A, CIMINO J J. A Learning Health Care System Using Computer-Aided Diagnosis [J]. Journal of medical Internet research, 2017, 19(3): e54.

[28] SHIN H C, ROTH H R, GAO M, et al. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning [J]. IEEE transactions on medical imaging, 2016, 35(5): 1285-98.

[29] HUANG S, CAI N, PACHECO P P, et al. Applications of Support Vector Machine (SVM) Learning in Cancer Genomics [J]. Cancer genomics & proteomics, 2018, 15(1): 41-51.

[30] ABDEL-NASSER M, MELENDEZ J, MORENO A, et al. Breast tumor classification in ultrasound images using texture analysis and super-resolution methods [J]. Engineering Applications of Artificial Intelligence, 2017, 59: 84-92.

[31] LIU Y, REN L, CAO X, et al. Breast tumors recognition based on edge feature extraction using support vector machine [J]. Biomedical Signal Processing and Control, 2020, 58.

[32] KRITI, VIRMANI J, AGARWAL R. Effect of despeckle filtering on classification of breast tumors using ultrasound images [J]. Biocybernetics and Biomedical Engineering, 2019, 39(2): 536-60.

[33] LIU X, LIU J, XU X, et al. A robust detail preserving anisotropic diffusion for speckle reduction in ultrasound images [J]. BMC genomics, 2011, 12 Suppl 5(Suppl 5): S14.

[34] XU H H, GONG Y C, XIA X Y, et al. Gabor-based anisotropic diffusion with lattice Boltzmann method for medical ultrasound despeckling [J]. Mathematical biosciences and engineering : MBE, 2019, 16(6): 7546-61.

[35] ZHANG Q, HAN H, JI C, et al. Gabor-based anisotropic diffusion for speckle noise reduction in medical ultrasonography [J]. Journal of the Optical Society of America A, Optics, image science, and vision, 2014, 31(6): 1273-83.

[36] LEY C, MARTIN R K, PAREEK A, et al. Machine learning and conventional statistics: making sense of the differences [J]. Knee surgery, sports traumatology, arthroscopy : official journal of the ESSKA, 2022, 30(3): 753-7.

[37] JIANG T, GRADUS J L, ROSELLINI A J. Supervised Machine Learning: A Brief Primer [J]. Behavior therapy, 2020, 51(5): 675-87.

[38] CARNAHAN B, MEYER G, KUNTZ L A. Comparing statistical and machine learning classifiers: alternatives for predictive modeling in human factors research [J]. Human factors, 2003, 45(3): 408-23.

[39] DIN N M U, DAR R A, RASOOL M, et al. Breast cancer detection using deep learning: Datasets, methods, and challenges ahead [J]. Computers in biology and medicine, 2022, 149: 106073.

[40] KALAFI E Y, NOR N A M, TAIB N A, et al. Machine Learning and Deep Learning Approaches in Breast Cancer Survival Prediction Using Clinical Data [J]. Folia biologica, 2019, 65(5-6): 212-20.

[41] BALKENENDE L, TEUWEN J, MANN R M. Application of Deep Learning in Breast Cancer Imaging [J]. Seminars in nuclear medicine, 2022, 52(5): 584-96.

[42] ANTROPOVA N, HUYNH B Q, GIGER M L. A deep feature fusion methodology for breast cancer diagnosis demonstrated on three imaging modality datasets [J]. Medical physics, 2017, 44(10): 5162-71.

[43] HAN S, KANG H K, JEONG J Y, et al. A deep learning framework for supporting the classification of breast lesions in ultrasound images [J]. Physics in medicine and biology, 2017, 62(19): 7714-28.

[44] FUJIOKA T, KATSUTA L, KUBOTA K, et al. Classification of Breast Masses on Ultrasound Shear Wave Elastography using Convolutional Neural Networks [J]. Ultrasonic imaging, 2020, 42(4-5): 213-20.

[45] ITOH A, UENO E, TOHNO E, et al. Breast disease: clinical application of US elastography for diagnosis [J]. Radiology, 2006, 239(2): 341-50.

[46] ZHOU B Y, WANG L F, YIN H H, et al. Decoding the molecular subtypes of breast cancer seen on multimodal ultrasound images using an assembled convolutional neural network model: A prospective and multicentre study [J]. EBioMedicine, 2021, 74: 103684.

[47] LI J, SUN B, LI Y, et al. Correlation analysis between shear-wave elastography and pathological profiles in breast cancer [J]. Breast cancer research and treatment, 2023, 197(2): 269-76.

[48] SONG E J, SOHN Y M, SEO M. Tumor stiffness measured by quantitative and qualitative shear wave elastography of breast cancer [J]. The British journal of radiology, 2018, 91(1086): 20170830.

[49] JIANG M, LI C L, LUO X M, et al. Radiomics model based on shear-wave elastography in the assessment of axillary lymph node status in early-stage breast cancer [J]. European radiology, 2022, 32(4): 2313-25.

[50] HUANG J X, LIN S Y, OU Y, et al. Combining conventional ultrasound and sonoelastography to predict axillary status after neoadjuvant chemotherapy for breast cancer [J]. European radiology, 2022, 32(9): 5986-96.

[51] FORTE A J, HUAYLLANI M T, BOCZAR D, et al. The basics of ultrasound elastography for diagnosis, assessment, and staging breast cancer-related lymphedema: a systematic review of the literature [J]. Gland surgery, 2020, 9(2): 589-95.

[52] QIAN X, PEI J, ZHENG H, et al. Prospective assessment of breast cancer risk from multimodal multiview ultrasound images via clinically applicable deep learning [J]. Nature biomedical engineering, 2021, 5(6): 522-32.