Review

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Deep Learning Theories and Methods for Breast Cancer Classification

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Review

Deep Learning Theories and Methods for Breast Cancer Classification

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Abstract: Breast cancer is a common malignant tumour and studies have shown that early and accurate detection is crucial for patients. With the maturity of medical imaging and deep learning development, significant progress has been made in breast cancer classification, which greatly improves the accuracy and efficiency of classification. This review focuses on deep learning, migration learning, GAN, and lifelong learning to elaborate and summarise the important roles arising from breast cancer detection. This review also examines the dataset and labeling issues required for breast cancer classification. In conclusion, at the end of the article, we look at future directions for breast cancer classification research, including cross-migration learning, multimodal data fusion, model interpretability, and lifelong learning, and also explore how to provide personalized treatment plans for patients.

Keywords: breast cancer; deep learning methods; image classification; GAN; transfer learning; lifelong learning

1. Introduction of Breast Cancer

Breast cancer is a type of cancer that forms in the cells of the breast tissue [1]. It is one of the most common cancers affecting women worldwide, although it can also occur in men, albeit less frequently. Breast cancer typically begins in the milk ducts (ductal carcinoma) [2] or the milk-producing lobules (lobular carcinoma) of the breast [3]. The disease can manifest as a lump or mass in the breast, but it can also spread to other parts of the body if left untreated.

The exact cause of breast cancer is not fully understood, but several risk factors have been identified. These include genetic mutations, such as mutations in the BRCA1 and BRCA2 genes, which increase the likelihood of developing breast cancer [4–6]. Other risk factors include a family history of the disease, age, gender, hormonal factors (such as early onset of menstruation or late menopause), and exposure to certain environmental factors. While these risk factors can contribute to the development of breast cancer, many cases occur without an identifiable cause [7].

Early detection is critical in the management of breast cancer [8]. Regular screening methods such as mammography, clinical breast exams, and breast self-exams can help identify abnormalities in the breast tissue. If breast cancer is suspected, further diagnostic tests, including biopsies, may be performed to confirm the diagnosis [9]. Treatment options for breast cancer vary depending on the stage and type of cancer but often include surgery, chemotherapy, radiation therapy, hormone therapy, targeted therapy, or a combination of these approaches. The choice of treatment is personalized based on the patient's specific case [10].

Breast cancer awareness and research have made significant progress in recent years, leading to improved diagnostic techniques and more effective treatments [11]. Early detection and advances in medical technology have contributed to higher survival rates for individuals diagnosed with breast cancer [12]. Supportive care and psychosocial services are also essential components of breast cancer treatment, as they address the emotional and psychological well-being of patients and survivors [13]. Public awareness campaigns, ongoing research, and regular screening continue to play a vital role in reducing the impact of breast cancer on individuals and communities worldwide [14].

The article structure of this review is distributed as follows: Section 2 focuses on an introduction to the functionality and application areas of deep learning, Section 3 describes the methodological techniques of deep learning for breast cancer detection, Section 4 describes an algorithm for detecting breast cancer using migration learning, Section 5 elaborates on the role of GAN in the process of breast cancer detection, Section 6 describes lifelong learning and the application of lifelong learning to breast cancer detection, and finally, conclusions and exploring future directions are given in Section 7. By reading this review, the readers can further understand the key role played by deep learning methods in breast cancer detection and the future research directions. Deep learning provides a powerful tool to improve early detection and accurate classification of breast cancer, which is expected to improve patient survival and treatment outcomes.

2. Deep Learning

Deep learning is a subfield of machine learning that focuses on the development and training of artificial neural networks, particularly deep neural networks [15]. It has gained widespread attention and prominence in recent years due to its remarkable ability to learn and make sense of complex patterns and data representations. Here are four key aspects of deep learning: neural network architectures, deep learning algorithms [16] and techniques, large-scale datasets, hardware acceleration, and distributed computing [17]. Neural network structures include many types of network structures and the following two network structures are very important in the problem of breast cancer classification.

2.1. Convolutional Neural Network (CNN)

CNN performs well in processing image data and extracting features and is therefore widely used in breast cancer classification tasks [18]. The CNN structure is divided into three layers, convolutional layer, pooling layer, and fully connected layer [19]. The network structure of CNN is shown in Figure 1 below. The convolutional layer is the most important in the CNN structure, which mainly uses a convolutional kernel to extract features from an image, generating a feature map that contains image edges, textures, and other features. Generally, multiple convolutional layers are stacked together to perform convolutional operations, and the more layers there are, the more abstract the extracted image features will be [20]. The pooling layer is mainly used to reduce the spatial size and dimension of the feature map, reduce the amount of computation, and reduce the complexity of the model. The commonly used pooling operations are mainly maximum pooling and average pooling. Each layer of the fully connected layer is closely connected, and each neuron is connected to all neurons in the previous layer. The processed abstract features are mapped to the output categories and the outputs are mapped to the category probability distributions by the softmax activation function.

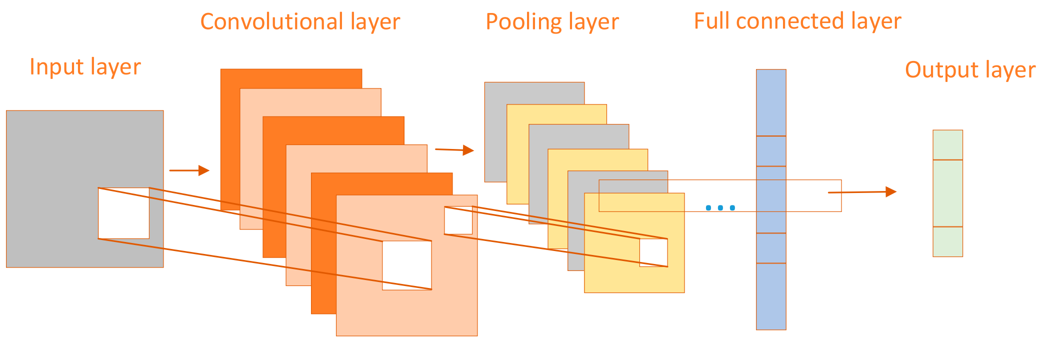

Figure 1. CNN structure diagram.

2.2. Recurrent Neural Network (RNN)

RNN is a deep learning model, and the model mainly contains a three-layer network structure, as shown in Figure 2. To maintain and update the internal state, the RNN has a unique cyclic structure, which is the core feature of the RNN [21]. This structure allows information to be passed from one-time step to the next and is therefore well suited for processing data with temporal or sequential relationships. So when breast data has a time series or sequence relationship, RNN can play an important role in the breast cancer classification task. Meanwhile, when training deep neural networks, the gradient is the signal used to update the model parameters. In the backpropagation algorithm, the gradient propagates from the output layer to the input layer. In RNNs, the gradient needs to be passed between time steps [22]. The problem is that when the network is very deep or the time step is very long, the gradient may become very small (gradient vanishing) or very large (gradient exploding), leading to invalid or unstable weight updates. To solve this problem, variants of RNN, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), have gradually emerged.

LSTM is an improved RNN architecture specifically designed to solve the problem of gradient vanishing and gradient explosion. LSTM introduces three gates (input gate, forgetting gate, and output gate) which control the flow of information about the internal state. Forgetting gates allow the network to forget unimportant information, input gates allow the network to accept new information, and output gates allow the network to output specific information. The design of these gates allows the LSTM to efficiently capture long-term dependencies while reducing the problems of gradient vanishing and gradient explosion [23].

GRU is another improved RNN architecture, similar to LSTM but more simplified. It includes reset gates and update gates that control the updating of the internal state. GRU has relatively fewer structures and therefore less computational overhead, but still effectively captures long-term dependencies and mitigates the gradient problem. These improved RNN variants (LSTM and GRU) have become the preferred choice when processing sequential data, especially in tasks where long-term dependencies need to be considered [24]. They have achieved significant success in areas such as natural language processing, machine translation, and speech recognition, as they allow models to better process and understand contextual information in sequential data while mitigating the gradient problem.

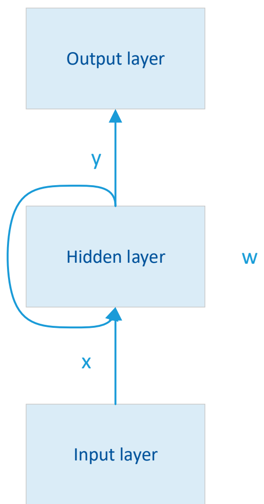

Figure 2. RNN structure diagram.

Where x, w, and y represent the matrices that linearly transform the vectors of the input, hidden, and output layers respectively.

At the core of deep learning are artificial neural networks, which are inspired by the structure and function of the human brain. These networks consist of interconnected nodes, or "neurons," organized into layers. Deep learning specifically refers to neural networks with multiple hidden layers between the input and output layers [25]. These deep architectures allow the network to automatically learn hierarchical features and representations from data, making them exceptionally powerful for tasks like image and speech recognition, natural language processing, and more.

Deep learning excels at feature learning and representation. Unlike traditional machine learning, which often requires manual feature engineering, deep learning models automatically extract relevant features from raw data [26,27]. This is particularly valuable when working with unstructured data, such as images, audio, or text. Deep neural networks can capture intricate patterns and abstract features at different levels of granularity, allowing them to handle a wide range of complex tasks.

Deep learning models require large amounts of labeled data for effective training. Some common breast cancer data sets are shown in Table 1. With the advent of big data and advances in computational resources, deep learning has become more practical and feasible. The availability of extensive datasets allows deep neural networks to generalize well to new, unseen data, leading to improved performance on various real-world applications. However, acquiring and preparing high-quality data remains a significant challenge in many deep-learning projects.

Table 1. Common breast cancer data sets.

Datasets	Source	Sample Size	Summary
WBCD	University of Wisconsin-Madison	The total number of samples was 569, of which 212 were malignant breast tumors and 357 were benign breast tumors	Each sample in this dataset includes a set of features describing the nature of breast tumor cells and an outcome label. Of particular importance is the fact that this dataset describes cytological features and does not contain breast images
UCI Breast Cancer Dataset	University of California, Irvine	The UCI breast cancer dataset includes about 569 samples	This dataset contains 30 features for describing the nature of breast tissue cells, which include the size, shape, texture, and uniformity of the nucleus
INbreast	Breast Centre Hospital, Porto, Portugal	This dataset contains 115 cases with 410 images	The dataset was obtained by performing an MRI scan of the breast. MRI images typically provide more detailed information about the breast tissue and can be used for breast cancer detection and analysis
BreakHis	Spanhol et al [28]. released in 2016	Contains 7909 breast histopathological images from 82 patients	BreakHis classifies breast lesions in detail, with benign lesions including adenosis (A), fibroadenoma (F), phyllodes tumor (PT), tubular adenoma (TA), ductal carcinoma (DC), lobular carcinoma (LC), mucinous carcinoma (MC), and papillary carcinoma (PC). Malignant lesions include ductal carcinoma (DC), lobular carcinoma (LC), mucinous carcinoma (MC) and papillary carcinoma (PC)
CBIS-DDSM	Selected and organized by a trained breast photographer	Contains 2,620 scanning film mammography studies	The dataset contains different types of image views and multiple cases. Among the images are digitized mammography images including different views such as orthostatic view of the breast, lateral view of the breast, and others.
MIAS	The UK National Breast Screening Programme Centre Fine Selection	The dataset contains 322 mammogram images	The dataset is relatively small and contains selected mammography images

Deep learning has found applications across various domains, including computer vision (e.g., image and video analysis), natural language processing (e.g., language translation and sentiment analysis), speech recognition, autonomous vehicles, healthcare (e.g., medical image analysis and drug discovery), and more. Its versatility and ability to handle large-scale, complex problems make it a valuable tool for solving a wide range of real-world challenges [29].

In all, deep learning is a subfield of machine learning that focuses on neural networks with multiple hidden layers. It excels at automatically learning features and representations from data, relies on large datasets for training, and has found applications in numerous domains [30]. Its capacity to tackle complex problems and extract meaningful patterns from diverse data types has

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made deep learning a transformative technology with far-reaching implications for industries and research fields.

3. Deep Learning for Breast Cancer Detection

Deep learning has demonstrated significant potential in improving the early detection and diagnosis of breast cancer [31–33]. Deep learning algorithms, particularly CNN [34,35], excel in image analysis. In the context of breast cancer, mammography and digital breast tomosynthesis (DBT) are commonly used imaging techniques. Deep learning models can be trained on large datasets of breast images, allowing them to automatically detect and classify suspicious features such as masses, microcalcifications, and architectural distortions. These models can assist radiologists by providing a preliminary analysis, reducing the risk of human error, and potentially increasing the accuracy of cancer detection [36]. A section of a malignant tumor of breast cells is shown in Figure 3.

Early detection is crucial for improving breast cancer outcomes. Deep learning can help identify subtle abnormalities that might be missed during routine screenings [37]. By analyzing mammograms and other breast imaging data, deep learning models can flag areas of concern, prompting further evaluation and potentially leading to earlier diagnosis and treatment initiation [38]. This can be particularly beneficial in cases where cancer is in its early, more treatable stages.

Deep learning can also contribute to risk assessment and personalized screening programs. By analyzing a patient's medical history, genetic information, and breast imaging data, deep-learning models can help identify individuals at higher risk of developing breast cancer [7,39,40]. This information can guide healthcare providers in tailoring screening recommendations, ensuring that high-risk patients receive more frequent or advanced screenings, while low-risk patients can benefit from less intensive screening protocols.

One challenge in breast cancer screening is the occurrence of false-positive results, which can lead to unnecessary anxiety, follow-up tests, and healthcare costs. Deep learning models can be trained to reduce false positives by refining their ability to differentiate between benign and malignant lesions [41]. By doing so, they can enhance the overall efficiency and cost-effectiveness of breast cancer screening programs.

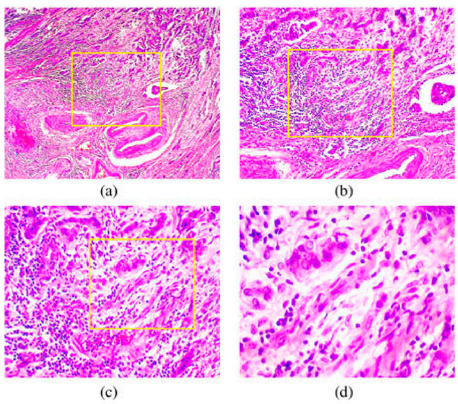

Figure 3. Sections of malignant tumors of the breast seen at different magnifications: (a) 40x, (b) 100x, (c) 200x and (d) 400x.

Deep learning can be integrated with other diagnostic tools and modalities. For example, it can assist pathologists in analyzing breast tissue samples (histopathology) by automating the identification of cancerous cells and assessing tumor characteristics [42]. Additionally, deep learning models can aid in the interpretation of breast MRI scans, offering a complementary approach to mammography and improving diagnostic accuracy in cases where MRI is more suitable.

There are several current studies based on deep learning for breast cancer detection, Mahoro, et al. [43] summarise different breast cancer screening methods to provide a foundation for accurate breast cancer classification. The paper also summarises the application of deep learning to breast

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imaging and presents the current challenges of combining AI and breast cancer clinical time. Umer, et al. [44] proposed a deep learning method for the classification of histopathological images to achieve classification detection of multi-tired breast cancer. The researcher developed a deep learning model with a feature fusion and selection mechanism called 6B-Net. The model has a short classification training time and can classify and detect the data efficiently. To solve the problem of manual classification of breast cancer regions by doctors, Ting, et al. [45] propose a CNN-improved breast cancer detection algorithm that achieves the classification of images into malignant, benign, and healthy patients, which is a triple classification problem. It achieves an accuracy of 90.50% and performs well in other evaluation metrics, achieving autonomy in breast cancer classification and reducing the burden on doctors. However, the accuracy of the method needs to be improved. Obayya, et al. [46] developed an algorithm for arithmetic optimization of histopathological classification of breast cancer (AOADL-HBCC) with an accuracy of 96.77%, which was developed based on deep learning. The authors used median filtering and contrast for the data enhancement process which helped to improve the accuracy of the algorithm. In addition to this, a DBN classifier with a hyperparametric optimizer is also used in the paper. Not only does deep learning have a great impact on breast classification, but the combination of deep learning and other methods for breast cancer detection has shown promising results. For example, Jabeen, et al. [47] proposed a method for breast cancer classification using a combination of deep learning and the best selected features, which has an optimal accuracy of 99.1%, outperforming most classification algorithms. The framework proposed in the paper is divided into five parts in total, first dataset augmentation is performed, feature extraction is performed in the middle two steps, then model optimisation is performed, and in the last step deep learning and the best selected features are fused which completes the task of classification of breast cancer.

4. Transfer Learning for Breast Cancer Detection

Transfer learning can play a pivotal role in improving the accuracy and efficiency of breast cancer detection through various approaches and applications [48–50]. Transfer learning can leverage pre-trained deep neural networks, such as CNN, that have been trained on vast image datasets [51]. These networks have learned to extract generic features from images, which can be highly valuable for breast cancer detection. By fine-tuning these networks on specific breast imaging datasets [52], such as mammograms or ultrasound images, transfer learning enables the extraction of relevant features associated with breast cancer, such as the shape, texture, and spatial patterns of abnormalities [53]. This reduces the need for manual feature engineering and accelerates the development of accurate detection models.

Breast cancer datasets, especially those with detailed annotations, can be limited in size and diversity. Transfer learning addresses this challenge by allowing the transfer of knowledge from larger and more diverse datasets. Models pre-trained on millions of images can be adapted for breast cancer detection, even when the specific dataset is relatively small [54,55]. This increases the efficiency of model training and enables the development of robust classifiers, particularly in cases where collecting large-scale, specialized medical datasets is challenging.

Transfer learning models benefit from the regularization effect of pre-training on large, diverse datasets. They tend to generalize better and are less prone to overfitting, even when dealing with limited medical data. By fine-tuning pre-trained models on breast cancer data, they can adapt their learned representations to the nuances of medical imaging, including variations in image quality, patient demographics, and disease presentation. This enhances the model's ability to make accurate predictions on new, unseen breast cancer cases [56].

Breast cancer detection often relies on multiple imaging modalities, such as mammography, MRI, and ultrasound. Transfer learning can be applied to each modality separately, and then the knowledge from these modalities can be fused to create a more comprehensive diagnostic model [57]. This fusion of information improves the overall accuracy and robustness of breast cancer detection systems, as it takes advantage of the strengths of each imaging technique.

Transfer learning models can be continuously updated and adapted to evolving knowledge about breast cancer and the availability of new data [58]. As medical understanding of the disease advances and more patient data becomes accessible, transfer learning allows for the seamless integration of these insights into the diagnostic process. This adaptability ensures that breast cancer detection models remain up-to-date and aligned with the latest research and clinical practices [59].

5. GAN for Breast Cancer Detection

Generative Adversarial Networks (GAN[24]) are primarily known for their ability to generate realistic data, but they can also play a role in improving breast cancer detection through various innovative approaches [60,61]. GAN can be used to augment medical imaging datasets, including those used for breast cancer detection. By training a GAN on a relatively small dataset of real mammograms or other breast images, it can generate synthetic images that closely resemble real cases. These synthetic images can then be added to the original dataset, effectively expanding the training data and diversifying it [62]. This augmented dataset can improve the robustness and generalization capabilities of machine learning models, leading to more accurate breast cancer detection algorithms.

GAN can be employed to fill in missing or incomplete parts of medical images. In the context of breast cancer detection, this can be particularly useful for cases where portions of an image are obscured or unavailable due to technical limitations. GAN can generate realistic replacements for the missing regions, allowing radiologists and algorithms to analyze more complete images, potentially leading to better diagnostic accuracy [63].

GAN can assist in tumor segmentation, which is a critical step in breast cancer diagnosis and treatment planning. GAN-based segmentation models can be trained to delineate the boundaries of breast tumors in medical images with high precision [64]. This segmentation can aid radiologists in quantifying the size and extent of tumors, providing valuable information for treatment decisions. The overall schematic of the GAN network is shown in Figure 4.

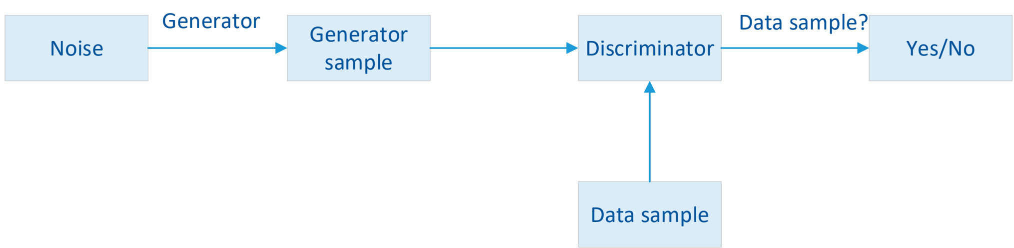

Figure 4. GAN structure diagram.

Medical images can be noisy due to various factors, such as imaging equipment limitations and patient motion. GAN can be used to denoise medical images by learning to distinguish between true anatomical structures and noise or artifacts. Cleaner images can improve the accuracy of breast cancer detection algorithms by reducing false positives and enhancing the visibility of subtle abnormalities [65–67].

GAN can create variations in breast images by altering factors such as tissue density, lesion characteristics, and image quality. This is particularly useful for testing the robustness of detection algorithms and ensuring they perform well across diverse clinical scenarios [68,69]. By simulating different clinical conditions, GAN can help identify and rectify potential weaknesses in breast cancer detection models.

6. Lifelong Learning for Breast Cancer Detection

Lifelong learning, a concept inspired by the way humans continually acquire and adapt knowledge throughout their lives, can significantly contribute to the improvement of breast cancer detection and diagnosis in several ways [70]. Lifelong learning systems can continuously update their knowledge and adapt to new information and techniques in the field of breast cancer detection [71]. As medical research advances and new diagnostic technologies emerge, these systems can integrate the latest findings into their algorithms. For example, when new biomarkers, imaging modalities, or diagnostic criteria are introduced, lifelong learning models can be retrained to incorporate this evolving knowledge, ensuring that breast cancer detection remains at the forefront of medical innovation.

Lifelong learning allows for the refinement and improvement of breast cancer detection models over time [72,73]. These models can start with a solid foundation, perhaps based on a large initial dataset, and then be fine-tuned and updated as new patient data becomes available. This iterative learning process leads to more accurate and reliable diagnostic models, which are essential for consistently improving detection rates and reducing false positives [74].

Breast cancer diagnosis often relies on multiple sources of data, such as mammograms, biopsies, genetic information, and patient medical histories [75–77]. Lifelong learning systems can seamlessly integrate and synthesize information from various modalities, creating a more holistic and comprehensive view of a patient's condition. By considering a wide range of data sources, these systems can offer more precise and personalized diagnostic recommendations.

Lifelong learning can facilitate patient-centered care by incorporating patient feedback and outcomes data into the learning process [78]. This allows the system to consider individual patient experiences, preferences, and responses to treatment, which can lead to more tailored and effective breast cancer detection and treatment strategies. Patient-centered approaches can improve patient satisfaction and overall healthcare outcomes.

Lifelong learning models can help reduce diagnostic delays by continuously optimizing the triage and prioritization of breast cancer cases [77,79]. By learning from historical data and adapting to changing trends, these systems can assist healthcare providers in identifying high-risk cases more quickly, ensuring that patients receive timely evaluations and treatments, which is crucial for better outcomes and survival rates.

7. Conclusion and Future Directions

In conclusion, deep learning has made significant strides in the field of breast cancer detection, offering the potential to revolutionize the way we diagnose and treat this disease. With its ability to automatically extract complex features from medical images, deep learning models have shown promise in improving the accuracy and efficiency of breast cancer detection. Additionally, transfer learning techniques and the integration of multimodal data have further enhanced the capabilities of deep learning algorithms in this domain.

The future of deep learning for breast cancer detection holds several exciting directions. Firstly, the development of more interpretable models will be crucial to gaining the trust of medical professionals and ensuring the transparency of decision-making processes. Explainable AI techniques will enable clinicians to understand and validate the decisions made by deep learning systems. Secondly, deep learning models could be applied to address the challenges of early detection and the identification of high-risk populations, allowing for more targeted and effective screening programs. Furthermore, the use of deep learning in predicting treatment responses and patient outcomes is an emerging area of research, which has the potential to personalize treatment plans and improve patient care.

Lastly, collaboration between researchers, clinicians, and AI experts will be essential for the successful integration of deep learning into clinical practice. Ensuring that AI models are rigorously evaluated, validated, and ethically deployed is critical for their adoption in healthcare settings. As the field continues to evolve, deep learning has the potential to make a profound impact on breast cancer detection, ultimately leading to earlier diagnoses, better treatment outcomes, and improved patient care.

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