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DEEP LEARNING METHODS FOR BREAST CANCER DETECTION AND CLASSIFICATION: A SYSTEMATIC REVIEW

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Abstract

The complicated structure of breast tissues makes breast cancer detection a major treatment hurdle. Over the past decade, the growth of artificial intelligence approaches, particularly deep learning models, has dramatically facilitated and enhanced the early diagnosis of breast cancer. Our survey complies with Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) criteria in order to guarantee the thorough gathering of recent and pertinent research on breast cancer detection and categorization. Our investigation commences by examining the different diagnostic methods, such as magnetic resonance imaging, thermography, mammography, and histopathology, as well as the corresponding characteristics of the imaging datasets. Breast cancer can be classified as benign, in-situ, or invasive, based on the manner in which malignant cells proliferate and disseminate throughout the body. The cornerstone of almost all classification systems lies in deep neural networks, particularly convolution neural networks, which employ transfer learning to attain superior outcomes with fewer training iterations. Vision transformers (ViT) have emerged as an innovative approach to deep learning models and are currently being utilized in various computer vision tasks. Nonetheless, we have observed a lack of adequate application of ViT in diverse breast cancer imaging, which could potentially inspire the development of novel classification systems.

Keywords: Breast cancer, CNN, Deep learning, Transfer learning, Vision transformers.

1. Introduction

Presently, breast cancer is the most common cancer in the world to be diagnosed, and it also accounts as the major cancer-related deaths in women [1]. Around 2.3 million women worldwide were diagnosed with breast cancer in 2020, and over 685,000 of those instances resulted in death, according to figures released by the World Health Organization (WHO) [2]. By 2030, the number of cases of breast cancer is likely to rise to 1.1 million, according to the WHO's International Agency for Research on Cancer (IARC), and the gap between developing and developed countries is expected to grow [3]. The abnormal proliferation of breast cells is known as breast cancer in medicine. Generally, they fall into one of three categories: invasive, in situ, or benign carcinomas [4]. Exceptional growths or other benign (non-cancerous) abnormalities in the breast tissue are known as benign breast problems. An early stage of breast cancer is called ductal carcinoma in situ. The cells in the breast's milk ducts are impacted by this illness. The milk duct lining cells develop into malignant tissue but do not move. Breast cancer that is invasive is the deadliest kind. The cancerous cells penetrate the duct wall, travel to lymph nodes, and even enter the bloodstream.

A lump in the breast or under the armpit is the most typical sign of breast cancer. Breast cancer rarely hurts, thus a lump that feels painless is far more suspicious of malignancy than one that hurts [5]. Medical imaging methods like mammography, tomography, ultrasound, and MRI (Magnetic Resonance Imaging) are frequently used to screen for and diagnose breast cancer [6]. When performed early in life, mammography is seen to be a safe and inexpensive technique, although it is useless for young girls with dense breasts. In women with dense breast tissue, breast ultrasonography is more sensitive than mammography at identifying lesions, nevertheless, it may not pick up on solid tumors or tiny abnormalities that are frequently seen by mammography. For women who have been diagnosed with breast cancer, a breast MRI is primarily utilized to determine the cancer's exact size. MRI provides better soft tissue contrast which can help to differentiate better between fat, water, muscle, and other soft tissue. However, MRI sometimes picks up other changes in the breast that are not cancerous [7].

Besides medical imaging, breast cancer can be screened by biopsy of breast nodules. It usually provides a correct and definitive diagnosis of breast cancer. Breast cancer detection faces several challenges, especially to differentiate between dense tissue and cancer. In fact, both dense tissue and cancer appear white in mammography, which makes breast cancer screening more difficult and increases the risk that cancer won’t be detected. These challenges motivate the application of artificial intelligence (AI) to give radiologists and oncologists a reliable diagnostic instrument. In this context, numerous Computer-Aided Diagnosis (CAD) systems have been created. To extract morphological and textural characteristics from breast images, they were first dependent on manually created feature extraction techniques such as Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG) [8]. Machine learning (ML) techniques like k-means, support vector machines (SVM), random forest, and naive Bayes have been used to understand intricate correlations between the collected characteristics in order to create accurate and dependable models for cancer diagnosis and prediction. The main disadvantage of machine learning is that it is a laborious process that takes a long time to complete. Deep learning (DL) techniques have transformed computer vision in recent years, with a wide range of applications ranging from semantic

segmentation and medical image analysis to object recognition and image categorization [9].

Deep learning algorithms are more versatile and adaptive than machine learning algorithms because they can learn from unlabelled or unstructured data, unlike classic machine learning algorithms that require laborious data classification [10]. Because DL models can automatically extract high-level features from breast images, they have been extensively used in the detection of breast cancer, and the results have been highly encouraging in terms of identifying cancer cells [11]. The objective of this research is to conduct an analysis of some previous studies in the field of deep learning models-based breast cancer detection and classification. We considered publications over the previous five years (conducted from 2019 to 2023). We also explore the difficulties and offer suggestions for further study. The following succinctly describes the primary contributions of this study: First, we provide a summary of the key methods used in the diagnosis of breast cancer. Secondly, we investigate the imaging datasets that were employed in this work. We also conducted an analysis of current breast cancer detection technologies and the outcomes they produced. Systems based on Convolution Neural Networks (CNN) and Vision Transformers (ViT) models are included in this study. Lastly, we determine the future paths that CAD-based techniques for breast cancer screening will take.

The remainder of this essay is structured as follows: The research plan and technique are presented in Section 2. The various methods used to diagnose breast cancer are covered in the third part. The most public breast cancer datasets are presented in Section 4. Section 5 reviews the different breast cancer detection systems and techniques. Finally, we relate challenges, and we highlight future directions.

2. Research Methodology

2.1. PRISMA flow diagram

We conducted this review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) as a guideline [12]. We searched the literature on machine learning techniques for breast cancer screening, mostly in the Scopus and Google Scholar databases. The search included studies published until the end of 2023. We used the terms ("machine learning") OR ("deep learning") OR ("detection") OR ("classification") OR ("prediction") AND ("breast") in the search query. The initial search identified 1200 articles from databases and 173 articles from other sources. We identified 1146 articles after removing duplicate articles. We rejected a total of 779 papers that addressed other general applications of machine learning in healthcare or oncology without a specific focus on breast cancer. Also, articles not written in English. As a result, we obtained 367 articles, then examined the titles and abstracts of the articles and discussed the criteria against which the review was conducted. We excluded traditional machine learning algorithms and articles without empirical results. The focus was only on deep learning techniques with articles that focused on the use of mammography, ultrasound, histopathology, and MRI techniques. In total, 60 articles were selected that met the review's inclusion criteria as shown in Fig. 1.

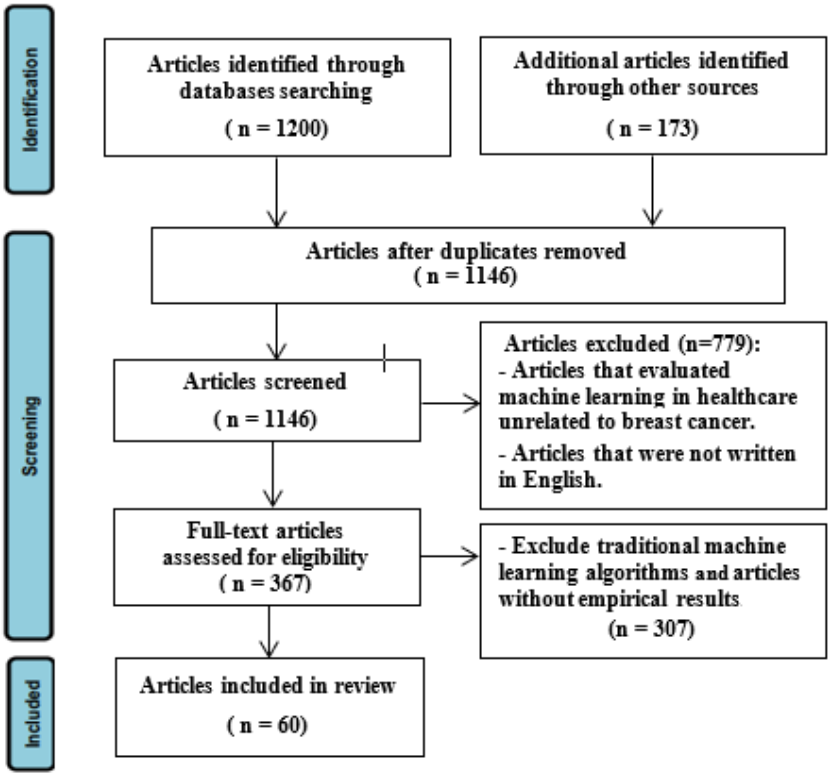


Fig. 1. PRISMA Diagram flow.

2.2. Statistical study

We conducted a statistical study based on the selected papers to show their distribution according to the year of publication, the medical imaging methods, and the deep learning models used. Figure 2 displays the results of these statistics.

2.3. Research questions

We created the following research questions to fulfil the primary goal of this systematic review:

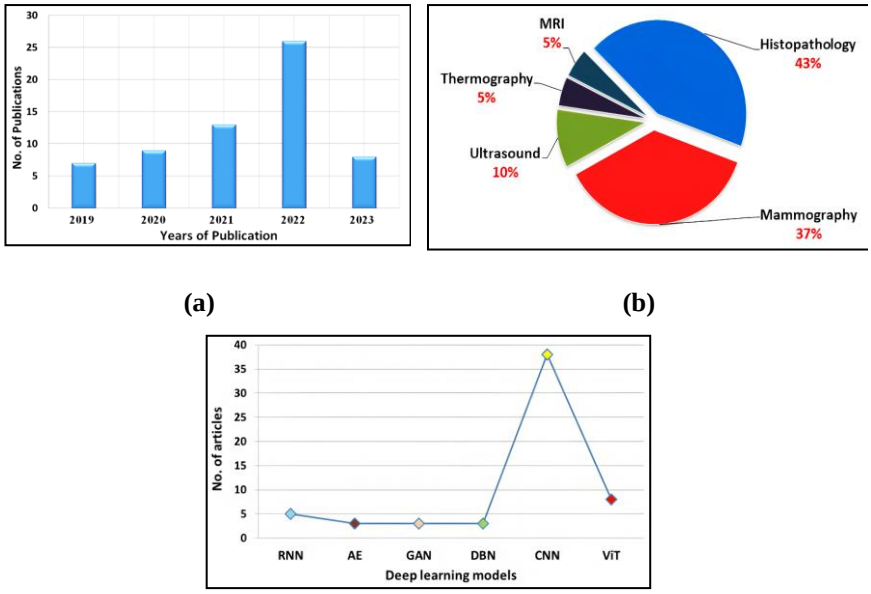
RQ1: Which medical imaging methods are frequently employed to diagnose breast cancer?

RQ2: Which popular datasets are used to identify breast cancer?

RQ3: Which deep learning methods are currently being used to classify breast cancer cases?

RQ4: In comparison to CNNs that are typically utilized, how well the Vision Transformer-based models do in a task that involves classifying breast cancer?

RQ5: What are the obstacles and potential paths for deep learning-based cancer detection techniques?



(a) **(b)**

(c)

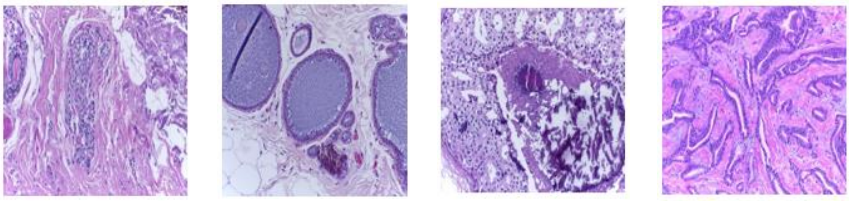
Fig. 2. Statistical study of the reviewed papers.

3. Breast Cancer Diagnostic Techniques

The most popular medical imaging methods for diagnosing breast cancer are covered in this section, including thermography, magnetic resonance imaging, ultrasound, mammography, and histology.

3.1. Histopathology (His)

The study of a tissue biopsy is known as histopathology. It might be advised if you have any questionable breast tissue, such as a breast lump, or if you exhibit other warning signs or symptoms of breast cancer (as shown in Fig. 3). A biopsy is a procedure where a sample of breast tissue is taken out for analysis. A pathologist, a medical professional with expertise in examining blood and bodily tissue, receives the tissue sample and uses it to make a diagnosis [13].

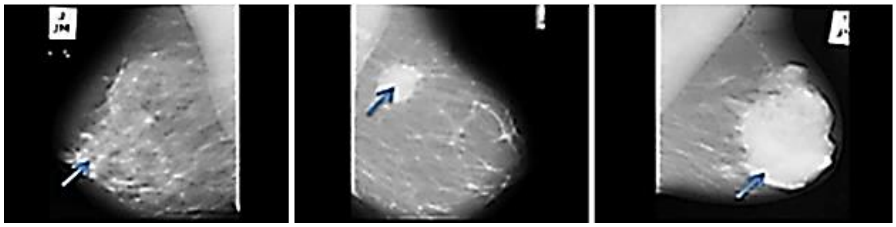


(a) Normal **(b) Benign** **(c) In situ** **(d) Invasive**

Fig. 3. Microscopic biopsy images from BACH database.

3.2. Mammography (Mg)

Low-dose X-rays are used in mammograms, a type of medical imaging procedure, to examine the breast for anomalies or indications of breast cancer. Compressing the breast between two plates and capturing X-rays of the breast tissue is a non-invasive treatment. Medical practitioners advocate mammograms as a useful screening method for early breast cancer detection [14]. It is among the most precise examination techniques and has produced excellent results when it comes to locating calcification agglomerations. Generally, women over 40 should consider it. Additionally, it is carried out when a certain breast area is monitored for a predetermined amount of time. Mammography images from the MIAS database are shown in Fig. 4.

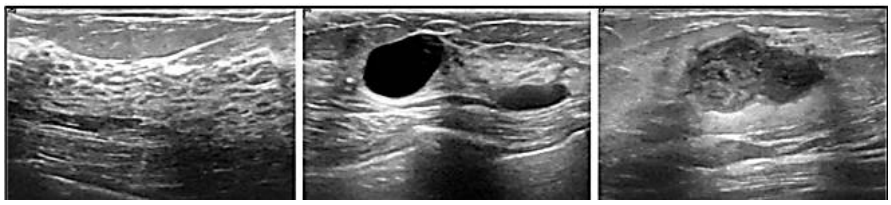


(a) Normal **(b) Benign** **(c) Malignant**

Fig. 4. Mammogram images from MIAS database.

3.3. Ultrasound (US)

Ultrasound is the most common supplement to mammography and may be the primary modality used to examine breast symptoms in women less than 35 years old. It is also the preferred imaging technique for pregnant or lactating women [15]. Furthermore, breast ultrasonography images are monochrome, have lower resolution, and can distinguish cysts from solid masses more accurately than mammography does. On ultrasonography, the cancerous regions appear as amorphous forms with hazy borders. On the other hand, breast ultrasound can reduce the number of needless biopsies by 40% and raise the total detection rate by 17% [16]. Breast ultrasonography employs sound waves rather than radiation to create images; there are no known dangers associated with this practice. Solid tumours or tiny masses that are frequently seen by mammography may go undetected by breast ultrasonography. The ultrasound may be less reliable if the patient is obese or has enormous breasts. Figure 5 shows breast mass ultrasound images.



(a) Normal **(b) Benign** **(c) Malignant**

Fig. 5. Breast mass ultrasound images.

3.4. Thermography (Thg)

Thermography is an infrared-based temperature measurement. Unlike other methods it is a passive, non-invasive, radiation-free method [17]. The fundamental tenet of thermography is that, at absolute zero, all living things produce infrared radiation. Infrared radiation is converted into electrical signals by an infrared thermal camera, which produces a thermogram. Because normal tissues have a different temperature scale than probable abnormalities, prospective abnormalities are highlighted and distinguished from them [18]. Angiogenesis, or the formation of extra blood vessels, occurs in conjunction with tumour growth. The growing tumour receives more oxygen and nutrients from the blood arteries, and as a result, the local temperature of that location rises in comparison to the surrounding tissues' temperature. This phenomenon may point to serious abnormalities at the breast level [19]. Figure 6 shows breast thermograms from Mastology Research Database.

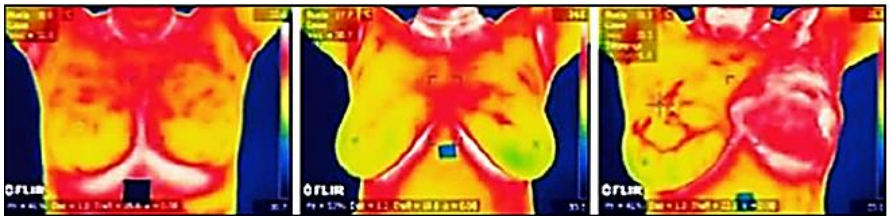
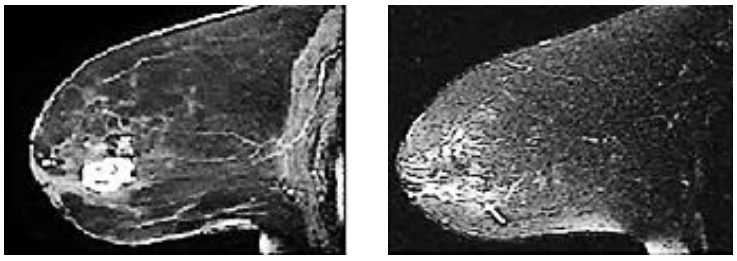


Fig. 6. Breast thermography from MRD database.

3.5. Magnetic resonance imaging (MRI)

Strong radio waves and magnetic fields are utilized in the process of magnetic resonance imaging (MRI), an imaging technique used for diagnostics that generates three-dimensional images [20]. Due to its remarkable sensitivity and efficacy in dense breast tissue, magnetic resonance imaging (MRI) possesses a broader range of clinical applications as an adjunct diagnostic method to mammography and ultrasound [21]. In relation to breast cancer, the overall sensitivity of MRI is approximately 90% in distinguishing between benign and malignant breast lesions, indicating that there is a possibility of misdiagnosing 10% of cancers [22]. Figure 7 represents MRI breast cancer images before and after chemotherapy.



(a) before chemotherapy **(b) after chemotherapy**

Fig. 7. MRI breast cancer images before and after chemotherapy [22].

4. Breast Cancer Datasets

Deep learning models require a huge lot of data to perform better. In this context, several imaging datasets related to breast cancer diagnosis and categorization are available. These databases are available to researchers for academic use and to further their study in breast cancer classification and interpretation. Some datasets, however, lack clinical information since they vary based on whether they are public or private and what kind of imaging technique was employed. The most popular datasets for breast cancer detection and classification are covered in Table 1.

Table 1. Breast cancer diagnosis datasets.

Dataset Name	Instances	Image Format	Classes	Published year
BreakHis [23]	7909	PNG	Benign, malignant	**2015**
Wisconsin Diagnostic Breast Cancer (WBCD) [24]	569	CSV	Benign, malignant	2015
Mammographic Image Analysis Society (MIAS) [25]	322	PGM	Benign, malignant, normal	1994
Digital Screening Mammography Database (DDSM) [26]	10,480	JPEG	Benign, malignant, normal	1999
Breast Cancer Image Dataset (CBIS-DDSM) [27]	3468	DICOM	Normal, benign, and malignant	2017
INbreast [28]	410	DICOM	Benign, malignant	2012
RIDER Breast MRI [29]	1500	DICOM	Normal, Abnormal	**2006**
DMR-IR [29]	5760	.JPG	Normal, Abnormal	**2010**
BACH [30]	400	TIFF	Normal, benign, in situ, invasive	**2018**
PatchCamelyon (PCam) [31]	327.680	--	Normal, Abnormal	**2016**

5. Literature Review of Breast Cancer Classification Systems

In this section, we examine the breast cancer classification schemes that were utilized in the articles under review. The utilization of deep learning models, which possess the ability to automatically extract high-level features from input images, serves as the foundation for most of these systems [15]. Deep learning techniques have demonstrated potential in various domains, including computer vision and medical imaging, encompassing Convolutional Neural Networks (CNN), generative adversarial networks (GAN), Autoencoders (AE), Recurrent Neural Networks (RNN), and recently, the Vision Transformers.

In the last decade, several deep learning models and especially CNN architectures such as VGG, ResNet, DenseNet, and GoogleNet achieved state-of-the-art performances in several computer vision tasks. These models are pretrained on a large set of images (ImageNet database), which allowed them to have a high generalization in different classification tasks. The concept of transferring knowledge of a model from one domain to another is called transfer learning. This technique is based on applying fine-tuning [32] i.e. preserving the extraction part of the model including the pretrained weights and adding some non-linear hidden layers according to the new classification task. Transfer learning offers several

benefits. It allows to accelerate the training time and achieves better results in fewer steps, even for fewer training images. In medical imaging, transfer learning can be applied by deploying models trained on other types of cancers as the start point of the training process [33]. In breast cancer images, transfer learning can have limits due to the diversity of breast image types, and because of the difference in the characteristics of breast cancer cells compared to others [34]. However, these disadvantages include the potential for limited generalization to new domains.

5.1. Convolutional neural networks (CNN)

CNN is a well-liked deep-learning technique that automatically extracts pertinent characteristics from input data by forming convolutional operations on it [35]. It has demonstrated excellent performance in various domains, including medical imaging, particularly in the diagnosis of breast cancer, where object identification, image classification, and image segmentation are possible. CNN automatically learns the hierarchical representations of features from the input data by taking the input image as a matrix of pixel values and assigning weights to the values [36]. It is made up of several layers, such as pooling, activation, and convolution layers.

By applying pertinent filters, convolution layers oversee learning features and capturing spatial correlations between features. To concentrate the treatment on the pertinent areas of the image, pooling layers decrease the spatial dimensionality of the characteristics. To create a one-dimensional vector with all pertinent features helpful for the classification task, the set of feature maps is first flattened in the extraction phase (Fig. 8).

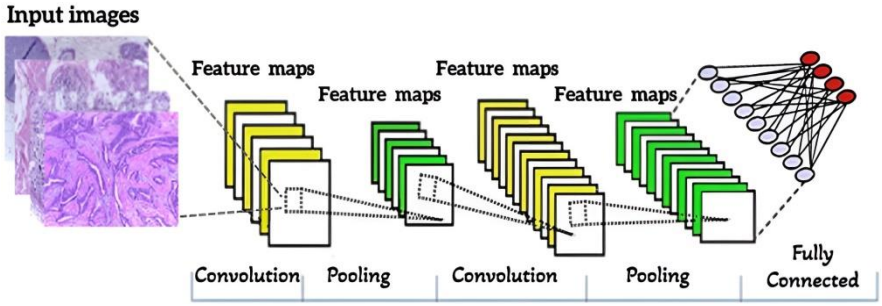


Fig. 8. CNN model illustration.

Using the attentional unit in a modified VGG-16 structure, Kalafi et al. [37] suggested a new framework for categorizing lesions related to breast cancer. The benefit of being able to differentiate between background and target lesions in ultrasonography is enhanced by the attention-dependent process. Additionally, to reduce model disagreement between nomenclature and identified lesions, the authors developed a new aggregated loss function. The network is optimized more quickly thanks to this integrated loss function. Using B and UMMC databases, the suggested model with features taken from VGG16 performed the best in the classification challenge, achieving a 93 % accuracy rate.

Singh et al. [38]. Using a variety of optimization techniques, they used a transfer learning strategy on the InceptionResNetV2 model that had already been trained. Their approach achieved up to 94% accuracy in detecting and classifying breast

cancers when evaluated on the CBIM-DDSM database. Mohamed et al., [17] suggested a two-pronged, fully automated technique for identifying and classifying breast cancer. First, the breast region is automatically extracted and isolated from the rest of the body using semantic segmentation using the U-Net network. Second, they classified normal and pathological breast tissues from thermal pictures using a neural network that was trained from scratch. Their method was evaluated using the DMR-IR database, and 99.33 % accuracy was attained. Another study applied transfer learning method to some pretrained deep neural networks, such as Inception-v3, ResNet50, VGG16, and Inception-ResNet [39]. With a 98.96% accuracy rate on the MIAS database, the VGG16 model yielded the best results.

Agarwal et al. [40] suggested using a patch-based CNN technique to automatically identify breast lesions in full-field digital mammography (FFDM). As feature extractors, they employed the pretrained VGG16, ResNet50, and Inception-v3. Using the Inception-v3 model on the INbreast database produced the greatest results, with a true positive rate (TPR) of 98%. Jiang et al. [41] included the Film Mammography number 03 dataset, a novel dataset of breast mammograms (BCDR-F03). To categorize segmented tumours observed on mammograms, they employed the Google Net and Alex Net models, and the resulting accuracies were 0.88 and 0.83 for Google Net and Alex Net, respectively. The most advanced deep learning models for CNN-based breast cancer diagnosis are displayed in Table 2. Deep learning-based systems employ two separate approaches for classifying breast cancer: binary classification and multiclass.

Table 2. Breast cancer systems-based CNN models in the selected paper.

Reference	Methodology	Imaging Technique	Datasets	Classes	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
[3]	Fuzzy merging with DCNN	His	IUHPL, TCIA, TMC, and BreakHis	B,M	98.62	94.7	96.4	93.5
[42]	Bayesian Network (BN) + CNN	Thg	DMR + images Astana Medical Center	Healthy, Sick	90.85	--	--	--
	MobileNet				93.8	97.4	88.5	94.9
[43]	EfficientNet-b0	Mg	CBIS-DDSM	B,M	95.4	95.4	--	95.37
			INbreast		99.7	99.55	--	99.57
[44]	Xception, NASNet, & Inceptoin_Resnet_V2	His	BreakHis	B,M	98	98	--	--
[45]	CNN + Attention Mechanism	Thg	DMR-IR	N,AN	99.46	99.71	99.71	99.49
[46]	Xception	His	BreakHis	Binary-class	100	100	--	100
				Eight-class	97.01	96.17	--	96.47

[47]	CNN with GRU	His	Kaggle	Invasive Ductal Carcinoma (IDC) (+,-)	86.21	85.60	84.71	88
[48]	CNNs + filter-based approach	Mg	INBreast	B,M	98.50	98.06	98.99	--
[49]	DCNN + KNN + Bayes + DT	Mg, His	BHI CBIS-DDSM BCW	N,B,M	99.14	99.40	99.87	99.54
[50]	GoogLeNet	Mg	MIAS and INBreast	N,B,M	91.92	91.70	97.66	91.92
[51]	ResNet50	Us	Mendeley MT-Small	B,M	99 98.7	100 97.4	98 96.8	98 96.6
[52]	AlexNet	Mg	DDSM CBIS-DDSM MIAS	N,AN	99.90 99.90 98	100 100 100	100 100 99	100 100 98.9
[53]	ResNet50 + Oversampling	Mg	MIAS	B,M	89.5	89.5	--	89.5
[54]	VGG-16	Mg	Mini-DDSM	N,B,M	65.70	91.24	90.35	--
[55]	ResNet	His	BreakHis	B,M N,B,M	99.7 97.81	97.53 97.65	97.8 97.31	-- --
[56]	VGG19+DensNet201	His	BreakHis ICIAR	B,M N, Invasive, In Situ, B	99.2 95.2	98.9 95.0	98.9 96.0	-- --
[57]	CNN	Thg	DMR	Healthy, Sick	97	83	100	--
[35]	UNet + MLP	His	BreakHis	B,M	95	95	95	95
[27]	EfficientNet	Mg	CBIS-DDSM	B,M	85.13	85.13	85.13	--
[58]	CNN	MR	DCE-MRI	Non-pCR, pCR	88	92.2	79.1	--
[59]	CNN	MR	I-SPY TRIAL	Response, No response	72.5	65.5	78.9	--
[30]	ConcatNet Baseline + (Nucleus, Mitosis, Epithelium, Tubule) U-Net	His	PCam	Normal, Tumor	84.1	82	87.8	--
[60]	Hierarchical CNN	His	BreakHis	B,M	95.48	93.55	--	--
[61]	Xception + SVM	His	BreakHis	B,M	96.25	96	--	96
[39]	VGG16	Mg	MIAS	N,B,M	98.96	97.83	99.13	97.66
[62]	Inception + Xception	His	BACH	N, Invasive	97.29	99.58	--	--

				, In Situ, B				
[63]	Combined DL Models	Mg	CBIS-DDSM	Masses, Calcifications	96.05	--	--	96
				B,M	85.71	--	--	84.21
[64]	MSF	His	BreakHis	B,M	98.23	98.15	--	98.08
[65]	ResNeXt50	MR	DCE-MRI	Non-pCR, pCR	77.2	78.1	76.9	--
[32]	Xception + InceptionV3	His	BreakHis	B,M	97.5	89	--	89
[66]	MVGG16	Mg	DDSM	Pathological , Non-pathological	94.3	93.7	--	93.6
[67]	3PCNNB-Net	His	BreakHis	B,M	97.04	97.14	95.23	--
[28]	YOLO-V4 + Inception v3	Mg	INBreast	Masses' location, B,M	97.86	100	--	94
[68]	ResNet50	His	BreakHis	B,M	99.75	99.37	99.18	--
[69]	CNN	Mg	MIAS	B,M	96.55	97.28	95.92	--
			DDSM		90.68	92.72	88.21	--
			INbreast		91.28	99.43	83.13	--
		Us	BUS-1		100	100	100	--
			BUS-2		89.73	93.33	86.14	--
[70]	DenseNet-201+ NasNetMobile, + VGG16+ Fine-tuned	His	BreakHis	B,M	99	99	--	99
			ICIAR	N, Invasive , In Situ, B	98	98	--	98
[71]	ResNet18 with block-wise fine-tuning, GCN	His	BreakHis	Binary-class	98.42	99.01	--	98.88
				Eight-class	92.03	90.28	--	90.77

N= Normal, B= Benign, M=Malignant, AN= Abnormal

5.2. Convolution recurrent neural networks (CRNNs)

Although images have spatial characteristics, along both the horizontal and vertical axes, the pixels are related in time. As a result, while creating a model, we need to consider both the temporal sequence link between the pixels and the spatial relationship of the image (Fig. 9) [72]. In fact, RNNs are specifically designed for processing sequential or time-series data, where the current input not only depends on previous inputs but also on the current hidden state of the network. RNNs have a memory mechanism allowing them to retain information from previous inputs

and take it into account when processing the current input. This memory is represented by a hidden state, which is updated at each step. RNNs are known to suffer from the vanishing or exploding gradient problem during training. This occurs when the gradient either shrinks or grow exponentially, making it difficult to propagate information across long sequences.

To lessen this issue, strategies like GRU (Gated Recurrent Unit) and LSTM (Long Short-Term Memory) [73]. Rarely is CRNN architecture used to detect breast cancer. We can refer to Patil and Biradar's [74] work, in which they retrieved the Gray-level run-length (GLRM) matrix and the Gray-level co-occurrence matrix (GLCM) from mammography pictures. Subsequently, the tumour segmented binary image is considered as input to CNN, and the GLCM and GLRM matrices are regarded as input to RNN for the identification of mammographic breast cancer. This model attains a 90.59 % accuracy rate. Table 3 shows some CRNN-based breast cancer detection works.

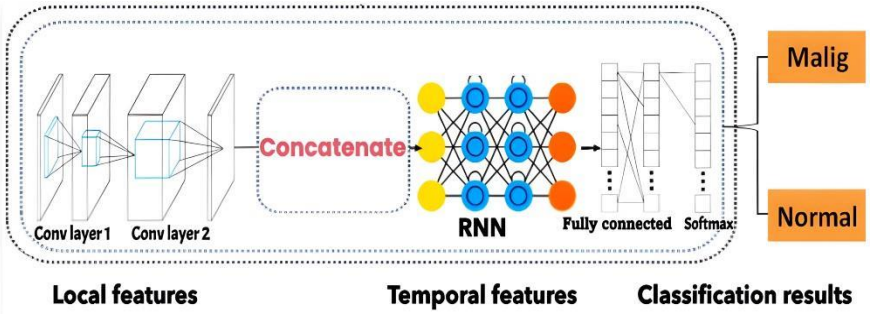


Fig. 9. CRNN architecture.

Table 3. Studies based on CRNN.

Work	Dataset	Architecture	Classification	Accuracy (%)
[72]	BACH	DenseNet121 + LSTM	Multiclass	**92**
	Bio-Imaging	RNN (LSTM) + Attention + TD		**100**
[75]	BreakHis	CNN + LSTM RNN	Binary Multiclass	**99** **92.5**
[76]	UCI repository	RNN	Binary	**97**
[77]	UCHC DigiMammo	CNN-RNN	Binary	**99.1**
[74]	NA	FC-CSO-CRNN	Multiclass	**90.59**

5.3. Generative adversarial networks (GANs)

Because GANs can examine, collect, and replicate differences within the training dataset, they are utilized for a restricted number of unlabelled datasets [13]. Deep learning-based generative approaches called Generative Adversarial Networks (GANs) are made up of two parts: a discriminator that determines if the examples generated by the generator are real or fraudulent, and a generator that creates new instances. These two elements are competitively trained at the same time. Whereas the discriminator model recognizes the difference between authentic and counterfeit images, the generator model creates new images that resemble the originals. GANs

may generate increasingly realistic and high-quality synthetic data during training, which can be applied to a variety of tasks like text synthesis, picture generation, and even video production. Figure 10 depicts the GAN's structure. Table 4 shows the works using GAN architecture for breast cancer detection tasks.

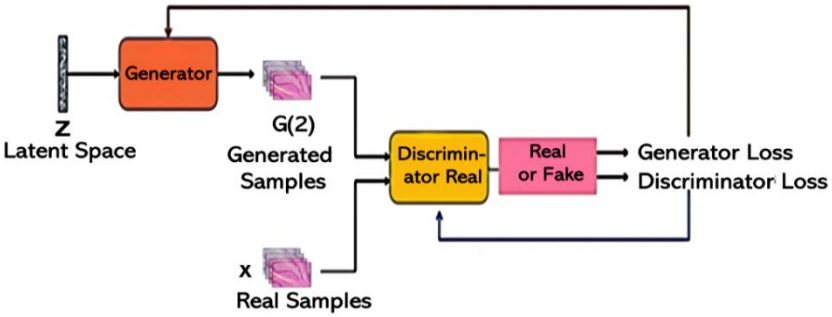


Fig. 10. Illustration of GANs.

Table 4. Studies based on GAN architecture.

Work	Dataset	Model	Classification	Accuracy (%)
[78]	DDSM	GAN	Multiclass	**80**
[79]	DDSM	GAN	Binary	**79.76**
[80]	DDSM	DCGAN + CNN	Binary	**87**

5.4. Auto-encoders (AEs)

Neural network architectures known as autoencoders (AEs) are employed in unsupervised deep learning [13]. By employing the encoder and decoding units, it duplicates the input values as the output [81]. The two main components are an encoder and a decoder. The most important properties of the input images are mapped by the encoder into a lower-dimensional latent space representation, and the decoder uses this latent representation to recreate the original input images [73]. Reducing error rates will let the autoencoder develop a compact representation while preserving crucial information. Figure 11 depicts the architecture of an autoencoder [82]. Table 5 lists a few works that use autoencoders for activities related to breast cancer.

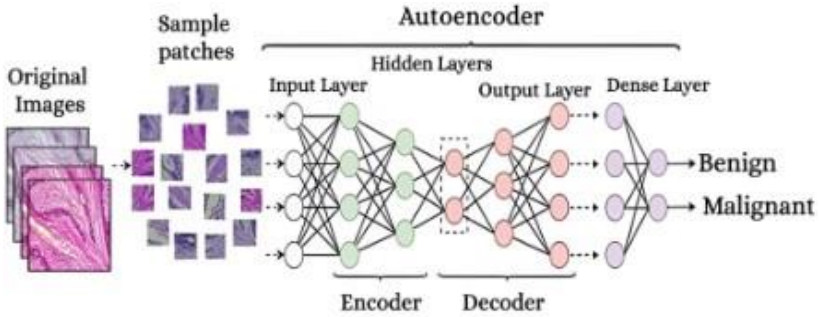


Fig. 11. Autoencoder illustration [13].

Table 5. Studies based on Auto-encoders.

Work	Dataset	Architecture	Classification	Accuracy (%)
[72]	WDBC	FE-SSAE-SM	Binary	**98.60**
[83]	BreakHis	AE + Siamese Network	Binary	**97.8**
[84]	Private	Deep AE	Binary	**96.58**

5.5. Deep belief network (DBN)

The Deep Belief Network (DBN) is an unsupervised and generative deep learning technique [13]. A Restricted Boltzmann Machine (RBM) is present in every layer [85]. Before classification, latent features are frequently extracted using RBM, an energy-based model that defines an input distribution [86]. The DBN can be taught for a variety of tasks, such as generation or categorization. By adding a classification layer to the pre-trained DBN and adjusting the weights using labelled input, further supervised learning steps can be carried out for classification (Fig. 12). The works based on DBN architecture for breast cancer diagnosis are shown in Table 6.

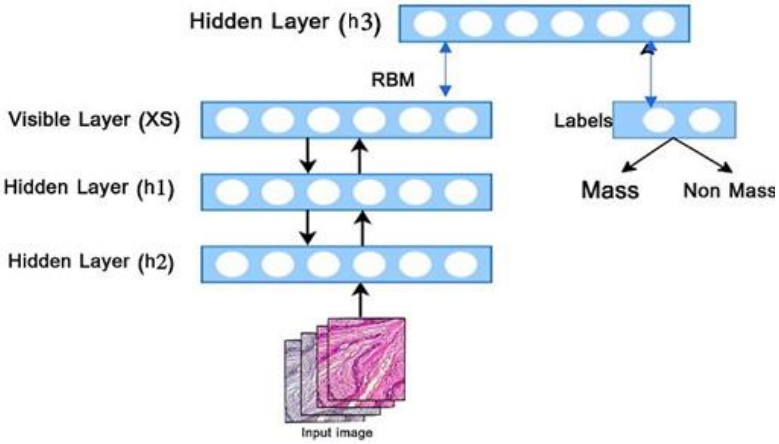


Fig. 12. Deep belief network illustration.

Table 6. Studies based on DBN architecture.

Ref.	Dataset	Architecture	Classification	Accuracy (%)
[87]	WDBC	DBN ELM- BP DBN BP-ELM DBN +GA	Binary	**99.75** **99.12** **98.54**
[88]	HUP, CWRU, CINJ, TCGA	DBN	Binary	**86**
[89]	INbreast MIAS	Fused FS + EBOG	Binary	**98.6** **98.85**

5.6. Transformers

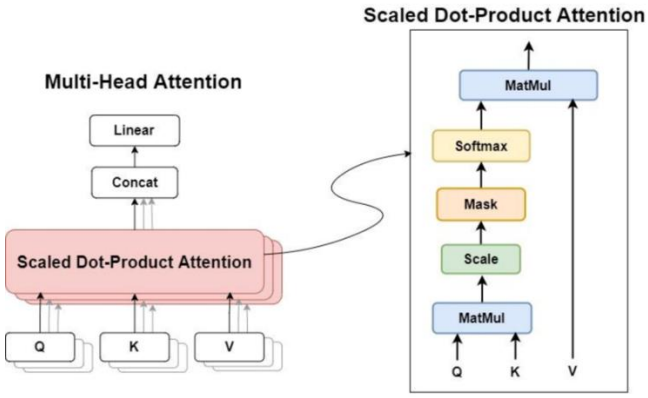
Recently, transformers have become one of the most architecture of deep learning models, particularly designed natural language processing. Additionally, it has lately been extensively used in a variety of computer vision applications, such as object detection [90], segmentation [91], image enhancement [92], and video processing [93], demonstrating its promise. Transformers enable the model to assess the significance of various input components during data processing because they are predicated on the idea of self-attention mechanisms. Conversely, the primary novelty of the transformer model lies in its attention mechanism, which allows the model to focus on distinct segments in the input sequence during prediction. Transformers are better able to identify long-term dependencies in data thanks to this attention mechanism. The Transformer was the first design to compute the representations of its input and output without the need of convolution layers by utilizing self-attention processes [94]. Transformers have a multi-layered architecture made up of an encoder layer and a decoder layer, which are created by piling Transformer pieces on top of one another. A multi-head self-attention mechanism sets each Transformer block apart [95].

5.6.1. Self-attention

An attention mechanism akin to CNN convolutions is called self-attention. It facilitates the identification of long-term connections between different picture regions [36]. The input is transformed into three distinct embedding matrices by the Self-Attention layer: the query matrix Q, which represents the input; the key matrix K, which represents the query that is compared with (Fig. 13(a)); and, lastly, the value matrix V, which indicates the relative relevance of each key to the query. The weighted total of all the value vectors is the Self-Attention layer's output. The scaled dot product between the query and its matched key establishes the weights assigned to each value (Fig. 13(b)). The key component of the Transformer (Fig. 13(a)) is Multi-Head Self-Attention (MHSA), which is made up of several Self-Attention heads concatenated to obtain the dependencies between the input sequence pieces. Each self-attention head has its own internal representation of the inputs, MHSA offers the advantage of allowing sequential and locational information to be learned in distinct representational subspaces for the model. Consequently, exchanging the data enables a more comprehensive knowledge of the connections among the image patches in a series [94-96].

5.6.2. Vision transformer (ViT)

Dosovitskiy et al. [95] presented a Vision Transformer (ViT), a transformer-based design, as a substitute for cutting-edge convolutional neural networks in computer vision-related tasks. ViT's self-attention layer makes it possible to embed information throughout the entire image globally. In order to reconstruct the image structure, the model also gains the ability to represent the relative positions of image patches. A picture is segmented into fixed-size patches in ViT, and these patches are linearly embedded together with position embeddings. After that, the generated vector sequence is delivered to a standard Transformer encoder (Fig. 14). The conventional method of classifying involves appending an additional learnable "classification token" to the sequence



(a). Multi-head attention **(b). Scaled dot product**

Fig. 14. Multi-head self-attention mechanism [96].

Chen et al., [97] used the multi-view Vision Transformer architecture, many mammograms from the same patient can be examined in a single investigation to capture the long-range correlations between them. Consequently, they learned distinct patch associations in four mammograms acquired from two-side (right/left) and two-view (CC/MLO) breasts using local transformer blocks. Concatenated outputs were fed into global transformer blocks from different angles and perspectives. The model was trained and tested using a five-fold cross-validation technique. The model outperforms the most advanced multi-view CNNs in case of classification, achieving an area under the ROC curve (AUC = 0.818 ± 0.039). Gheflati et al., [98] employed a pre-trained ViT model with an AUC of 95% to categorise breast US pictures using various augmentation techniques. As a result, the model achieved 86.7 % accuracy. Yu and Li suggested a transformer-based approach for classifying breast cancer without the need for big datasets [99]. Via a supervised phase, the network automatically extracts features from images of predetermined sizes, presenting the outcome as a probability matrix as either a positive sample (malignant) or a negative sample (benign). Using the publicly available BreakHis dataset, the model is trained from scratch to an accuracy of roughly 89%. Table 7 shows the state-of-the-art deep learning techniques that gave promising results in vision-transformer-based breast cancer classification.

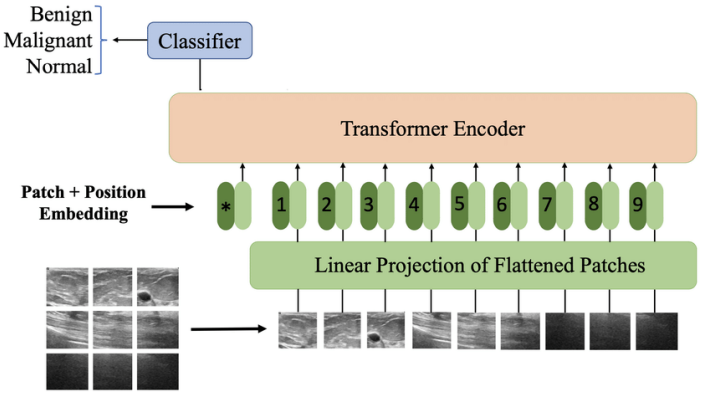


Fig. 14. Vision transformer model architecture.

Table 7. The ViT architectures used in the selected papers.

Work	Methodology	Imaging Technique	Datasets	Class	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
[97]	Two-view DeiT-tiny	Mg	Private	Binary	**77.0± 1.2**	0.726± 0.063	0.814± 0.057	0.757± 0.022
[98]	ViT	US	BUSI+B	Multi-class	**86.7**		AUC 95	
[99]	CCT2 2-64	His	BreakHis	Binary	**89.4**	89.42	AUC 92.45	
[100]	Pyramid ViT	Mg	DDSM	Binary	**0.78 ± 0.02**	0.78 ± 0.02	--	0.78 ± 0.01
[101]	PTN + distillation	Mg	Private		**0.794± 0.06**	--	--	--
[102]	CT + ViT + ATS	US His	BUSI BreakHis	Multi-class	**95.29** **98.12**	96.01 98.65	-- --	96.15 98.41
[103]	MultiNet-ViT	His	BreakHis	Multi-class	--	94	--	94
[104]	BEiT and RNN-LSTM	US His	BUSI NA	Multi-class	**99** **91**	100 100	100 68.28	98.8 89.18

6. Deep Learning Models Comparison

Considering the deep learning techniques applied for breast cancer detection and diagnosis, we present a comparison of these models in terms of their advantages and disadvantages. Table 8 shows a brief overview of these models.

Table 8. Comparison of the deep learning models under consideration.

Model	Advantages	Disadvantages
CNN	- High accuracy in image diagnosis due to spatial hierarchy learning. - Parameter sharing reduces overfitting risk. - Performance is best with pre-trained models.	- Requires large datasets. - High computational cost, especially with deeper networks.
CRNN	- Combines spatial and temporal feature learning, making it suitable for sequential data.	- Training the model is intricate and requires a significant amount of time. - The model is prone to experiencing issues such as vanishing or expanding gradients. - Excessive utilization of resources
GAN	- Can work with unlabelled data. - Highly effective at generating realistic synthetic data.	- The training and tuning process is quite complex. - Evaluating the obtained data is challenging.
AE	- Beneficial for reducing dimensionality and extracting features. - Beneficial for identifying and detecting anomalies.	- Susceptible to overfitting. - Limited application in classification tasks for breast cancer.
DBN	- Unsupervised pre-training. - Effective features extraction. - Reduces overfitting.	- Slow and computationally expensive training. - Harder to implement and tune.
ViT	- Utilizes self-attention to capture global dependencies. - Highly scalable for large datasets.	- Requires very large datasets for effective training. - High computational and memory costs. - More complex to train and tune compared to CNNs.

7. Discussion and future directions

Our review cites various deep learning models that automatically explore and extract complex features from various breast cancer images, features that can be challenging for human experts to detect. Overall, this review elucidates the persistent and concerted efforts undertaken within the scientific community aimed at enhancing the precision and operational efficiency associated with the diagnostic processes for breast cancer detection. We discuss a variety of deep learning models (CNNs, GANs, AEs, CRNNs, DBNs, and ViTs) that have the potential to develop more powerful and efficient classification systems. However, our review also identifies several limitations in current deep learning models. These obstacles encompass various constraints, including difficulty in generalizing to different types of breast cancer data, as well as interpretability and explanation issues. Deep learning models are often seen as black boxes due to their complex nature [105]. Another challenge is data efficiency, as training these models requires a lot of labelled data, which can be expensive and time-consuming. Although deep learning architectures have demonstrated robust performance, they are also resource-demanding and require substantial computational processing.

Convolutional neural networks (CNNs) have been widely used in the literature due to their ability to capture spatial hierarchies in images. Generative adversarial networks (GANs) offer a unique approach by generating synthetic data to augment training sets, thus addressing the challenge of limited labelled data. Autoencoders (AEs) are also used for dimensionality reduction and feature learning, enabling the extraction of salient features from high-dimensional data. On the other hand, convolutional recurrent neural networks (CRNNs) combine the strengths of CNNs and recurrent neural networks (RNNs) to handle sequential data, making them suitable for analysing temporal patterns in breast cancer imaging. Deep belief networks (DBNs) provide a probabilistic framework for learning hierarchical representations, which can be useful for unsupervised learning tasks. Vision transformers (ViTs) offer a new architecture that focuses on capturing global dependencies in images, providing a different perspective compared to the localized approach of CNNs.

Considering the future directions of developments and innovations in deep learning models specifically designed for breast cancer diagnosis, they should prioritize increasing the transparency of the models to make decision-making processes more understandable, thereby increasing clinical decision-making. Methodologies that enhance the effectiveness of model training should be developed to minimize the use of resources and processing power. Furthermore, it is necessary to utilize a variety of data types, which may include different forms of imaging data, comprehensive genetic information, and detailed diagnostic reports, to build comprehensive models that will significantly enhance the accuracy of diagnostic results.

8. Conclusion

In this work, we present a systematic review of breast cancer diagnosis based on deep learning models as well as different imaging techniques. The review results generally show that convolutional neural networks are the most widely used models

in our study, with a notable focus on the use of a transfer learning approach. Attention-based vision transformers have also been shown to be a new and innovative direction in this field. Moreover, advances in medical imaging technologies have the potential to improve diagnostic accuracy by generating more meaningful data, ultimately leading to the development of new CAD systems based on deep learning models to help radiologists and physicians make more accurate and efficient diagnoses, which will help improve clinical decisions.

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