Breast Cancer Classification Using Convolutional Neural Network: a Systematic Literature Review

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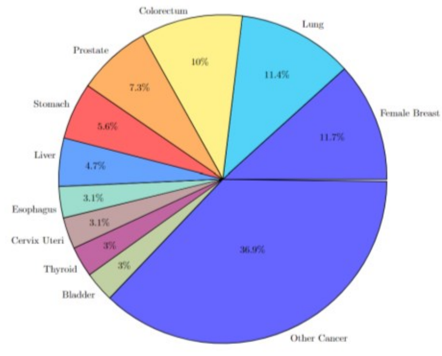
***Abstract*—Breast cancer is a prevalent disease affecting millions of women around the world. A key factor in improving the outcome of patients with breast cancer is early detection and classification. The use of convolutional neural networks (CNNs) has shown promising results for the analysis of various medical images, including the classification of breast cancer. This paper presents an overview of the breast cancer classification problem and demonstrates how a CNN can be effectively utilized for this task. Additionally, numerous papers have been presented and compared in terms of CNN structures, datasets, images, and accuracy. Different CNN models have been found to be effective at detecting breast cancer, which affects its accuracy. It should be recognized, however, that the accuracy of this algorithm depends on both the size of the dataset and the number of images that are used. As a result, it can be concluded that the number of images, datasets, or even the CNN approach can be used case-by-case to have higher accuracy. Finally, the results of accuracy should be expanded based on the analysis of one parameter in upcoming research. As soon as the best accuracy has been achieved, additional parameters may be added.**

Keywords—Breast Cancer, CNN, Classification, Deep Learning, Accuracy.

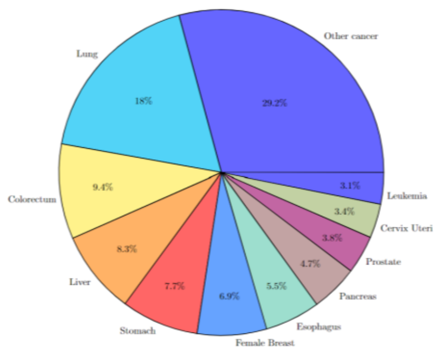
I. INTRODUCTION

Worldwide, cancer is regarded as one of the most feared diseases and a major roadblock in the extension of life expectancy [1]. Globally, there are an estimated twenty million newly diagnosed cancer cases and ten million cancer-related deaths. Over the next two decades, the cancer burden is expected to increase by approximately 60%, putting further strain on health facilities, communities, and individuals. Approximately 30 million new cancer cases are predicted to be added to the global burden by 2040, with the majority of these cases occurring in low- and middle-income countries [2]. The Breast Cancer Organization [3] reports that breast cancer represents 12.5% of all new cancer cases each year. Approximately one in eight women will be diagnosed with breast cancer at some point in their lives by 2023, according to the American Cancer Society. Men have a lifetime risk of breast cancer of 1 in 833 (0.12%) [4]. International Agency for Research on Cancer (IARC) data for GLOBOCAN 2020 shows that 185 countries have the highest incidence and prevalence of breast cancer [5]. As shown in Figure 1, different types of cancer are associated with varying levels of incidence and mortality.

As one of the most common diseases in the world, breast cancer is without a doubt one of the most prevalent. A growth of abnormal tissue occurs in the milk duct and then spreads to the breast tissue, leading to the development of cancer. Cancerous cells invade and grow within the ducts, resulting in invasive ductal carcinoma (IDC). Most cases of breast cancer are caused by invasive ductal carcinomas, which account for almost 80% of the cases. Approximately 80% of patients who are diagnosed with IDC at an early stage will survive the illness. Undiagnosed cancer is, however, capable of spreading to other parts of the body or to neighboring tissues if it is not detected [6]. Breast cancer has been associated with a number of factors, including age, obesity, harmful alcohol consumption, family histories of breast cancer, radiation exposure, reproductive history (including when women began menstruating and when they became pregnant), tobacco use, and hormone therapy for postmenopausal women, among others. Recent research has shown that approximately half of all cases of breast cancer are not associated with any identifiable risk factors other than being female and older than 40 years of age. Women are more likely to contract breast cancer than men, owing to the fact that their gender is among the strongest risk factors. Men are estimated to develop breast cancer at some point during their lifetime at a rate of approximately 0.5 to 1%. Both men and women are treated similarly for breast cancer, based on the same basic principles [7].



(a) Incidence rate



(b) Mortality rate

Fig. 1. Variations in cancer (a) incidence, and (b) mortality among different types of cancer (2020) [5].

Depending on the type of breast cancer, there are two categories, which are benign and malignant. Figure 2(a), 2(b), and 2(c) show three cases of ultrasound (US) images of the breast which are the benign tumors, the malignant tumors, and the normal breast [8], respectively. Breast cancer can be diagnosed and analyzed using several imaging modalities. These modalities are as follows:

1. Screen-film mammography (SFM) is an important imaging technique for detecting breast cancer early in its development. There are, however, some disadvantages associated with SFM as well. As a first concern, SFM has a low sensitivity for detecting breasts with dense glandular tissue [9]. There is a possibility that it is due to the film [10]. Once a film has been completed, it cannot be improved. Therefore, there is sometimes a lack of contrast in the images.

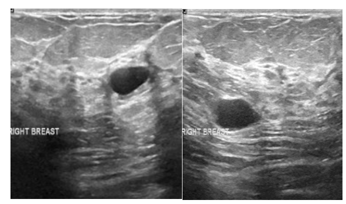
2. A digital mammogram (DM) is one of the most effective imaging tools for detecting breast cancer at an early stage. One of its strengths is the ability to selectively enhance the contrast of images within dense parenchymal areas [9]. DM, however, has limitations. Due to its low specificity [11], DM can cause some biopsies. There is also the risk of high radiation exposure for DM patients [9].

3. Magnetic resource imaging (MRI) can diagnose high-risk patients and provide a clinical diagnosis. In terms of breast cancer, MRI is very sensitive. A few problems still exist with MRI. The detection cost of MRI is higher than that of DM [12]. Although MRI is highly sensitive, it is not very specific [12, 13].

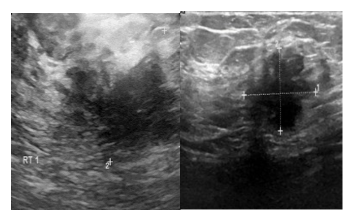
4. Ultrasound (US) is a common method for diagnosing breast cancer. Using ultrasound does not expose you to ionizing radiation. Therefore, ultrasound is safer and costs less than SFM and DM. However, ultrasound relies on the operator to deliver accurate images. In other words, how well ultrasound detects and differentiates breast cancer lesions depends greatly on the operator [14].

5. Digital breast tomosynthesis (DBT) is another option, which allows for a reduction of imaging times and a more detailed image of dense breast tissue than is possible with traditional mammography. In the case of DBT, there is a possibility that malignant calcification will not be detected during the slice plane. In addition, reading it takes longer than DM [15].

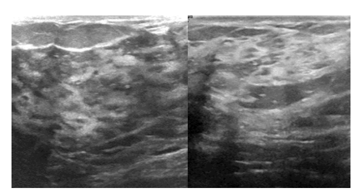
6. A histopathological image (HP) can provide insight into the structure and shape of cells. There is, however, a cost associated with this procedure, and it is invasive [16, 17].



(a) Benign



(b) Malignant



(c) Normal

Fig. 2. Ultrasound images of the Breast, (a) Benign tumor images, (b) Malignant tumor images, and (c) Normal breast images [8].

In recent years, new and improved techniques have been developed in order to prevent, diagnose, categorize, and treat breast cancers in a more effective and efficient manner. As a part of the medical imaging field, one of the most effective tools for detecting and diagnosing diseases early on is the use of computer-based diagnostic tools (CAD). With CAD binary classification, breast results are automatically categorized according to their severity by utilizing intelligent approaches. These imaging techniques may help doctors detect breast cancer earlier by assisting with the early detection of the disease. Since predicting detection and treatment of cancer is very important, many machine learning (ML) algorithms have been developed for cancer detection and classification research [18]. Besides their usefulness for computer vision, convolutional neural networks (CNNs) also have outstanding capabilities for assisting in image classification, which is difficult for deep neural networks [19]. The second and third sections provide a brief overview of the CNN model as well as a brief review of the literature on its use in breast cancer classification. The fourth section outlines the reasoning behind the CNN model used in breast cancer, as well as the challenges that they face. The fifth section outlines the conclusions derived from the results.

II. CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional neural networks (CNNs) are deep learning algorithms that can be used to perform similar tasks, such as classifying images and identifying objects. A CNN is composed of three layers, namely convolutional, pooling, and fully connected. As the input data is fed into the learning process, these layers are able to recognize features and hierarchies. Figure 3 illustrates the structure of the layers of a convolutional neural network.

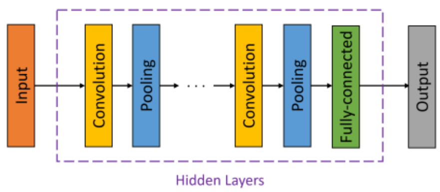


Fig. 3. The convolutional neural network structure.

In CNNs, convolutional layers represent the core building blocks that are used to extract features. As part of convolution operations, high-level features are extracted from input images to facilitate more sophisticated processing. A large image "input" can be processed by creating a small section and passing it through all the points within the image to produce output. At any point during their passage, they will have been convolved into a single position (output) when they pass through. Basically, it is the small areas of an image called filters (kernels) that pass over the larger areas of an image, thereby filtering it. Equation (1) calculates the output size of a convolutional operation.

$$O = 1 + \frac{(I - F) + 2P}{S} \tag{1}$$

where O×O is the output size, I×I is the input image size, F×F is the filter size, P represents the padding where padding refers to the additional pixels that are used to augment the input image around the edges, and S represents the stride, where it refers to the regularity of each step size in the sliding of the convolution filter. Figure 4 illustrates the convolution process. Figure 4 shows that padding and stride have been set to 0 and 1, respectively. I = 7, F = 3, P = 0, S = 1, thus O = 5.

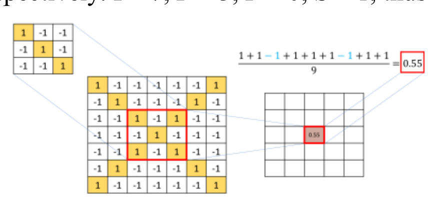


Fig. 4. Convolutional Layer process.

Pooling Layers: Similarly, to convolutional layers, pooling layers reduce image size while preserving their significant characteristics. Basically, pooling is down sampling. It is a term that refers to the output of a convolutional algorithm that is subsampled, which is achieved by taking a relatively small area of the output and sampling it. Pooling refers to different pooling techniques, such as maximum, mean, average, etc. The maximum pooling strategy involves taking the maximum value from a particular filter region, whereas the average pooling strategy involves taking the average value from a particular filter region. Figure 5 shows the max and average pooling.

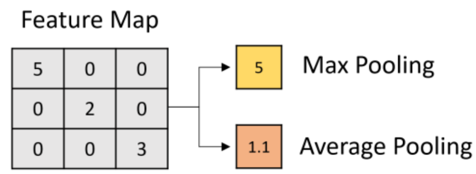


Fig. 5. The process of max and average pooling.

In the fully connected layer, the input image is classified into labels. The input data is eventually classified according to the desired label by virtue of the information obtained from the previous layers, i.e. the convolution layer and the pooling layer, being connected to the output layer.

It is critical to note that in the fully connected input layer, the output of the previous layers is "flattened" into a single vector, which may then be used to input the next layer. The first fully connected layer applies weights to feature analysis inputs to predict the correct label. A fully connected output layer gives each label's probability. As part of the Deep Neural Network classification section, the flattened layer, fully connected layer, and Softmax layer come together.

III. BREAST CANCER CLASSIFICATION USING CNN

CNNs have been used in a number of studies to classify breast cancer based on the type of cancer. The purpose of this section is to provide an overview of the existing CNNs that have been developed for the classification of breast images.

Sharma and Kumar [20], presented three basic data manipulation methods that could be applied to convert breast cancer numerical tabular data into images, namely equivalent bar graphs, normalized distance matrices, or a combination of these (bar graphs, distance matrices, and normalized numeric data). In order to construct CNNs, they used an architecture called VGG16. A backpropagation neural network is used to classify the images using various features extracted from the images, in order to obtain the labels for each class. Srikantamurthy, et al. [21] developed a hybrid model for categorizing four benign and four malignant breast cancer subtypes, which combines a convolutional neural network (CNN) with a long-short-term memory recurrent neural network (LSTM RNN). There was a comparison between the VGG-16, ResNet50, and Inception models that were compared to the hybrid CNN-LSTM model that was proposed. There were three different optimization methods that were used to generate models: Adam, Root Mean Square Propagation, and Stochastic Gradient Descent, each of which used varying epochs. Based on the results of both training and validation sets, the Adam optimizer was shown to be the most efficient and accurate optimizer, providing the highest accuracy level and minimal model loss. There was an overall accuracy of 99% for the hybrid CNN LSTM model when it came to the binary classification of benign and malignant cancers. As well as this, the accuracy of multi-class classifiers for benign and malignant cancer subtypes was found to be 92.5% in the study.

It has been proposed by Leow, et al. [22] that five types of pre-trained CNN models can be used to classify the histopathology of benign and malignant breast cancers. Among the machine learning algorithms used in this study were ResNet-50, VGG-19, Inception-V3 and AlexNet, and ResNet-50 was used as a feature extractor as well. When a feature is extracted from an image, it is passed on to a machine learning algorithm, in this case a random forest (RF) and k-nearest neighbor (KNN) algorithm, for classification. Thus, ResNet-50 is considered as the most accurate algorithm for classifying colored images as a result. Using CNNs, Iloghalu, et al. [23] developed a deep-learning model for predicting and categorizing breast cancer in a timely manner. A user-friendly interface is also provided as part of their breast cancer prognosis services, which allows users to upload images of breast cancer specimens and get predictions about the presence or absence of the disease, as well as estimates of the likelihood of occurrence. Alanazi et al. [24] proposed an approach to predicting breast cancer with the use of CNNs. This approach was proven to be more accurate than traditional machine learning approaches, reducing the possibility of human error and improving the diagnostic efficiency as compared with traditional methods.

According to Kumar, et al. [25], a soft-voting CNN model based on seven CNNs was developed. A number of transfer learning models are used in this method, including the VGG 19 (with and without data augmentation), the VGG 16 (without the use of data augmentation), the CNN with four convolution layers, the CNN with five convolution layers (with the use of data augmentation), and the Xception. The accuracy rate of the system is 96.91%. Guleria, et al. [26] proposed combining variational automatic encoding algorithms with denoising auto-encoding algorithms for reconstructing breast histopathological images. Using Kaggle data, CNN was used to predict whether a specific class of data belongs to the cancerous or non-cancerous category. According to the results of the study, the accuracy rate reached 73%.

In regards to the classification of breast histopathology images, a new hybrid method has recently been proposed by Sanyal, et al. [27], which is based on an innovative hybrid approach. Several CNN architectures have been fine-tuned to be the best supervised feature extractors, and a set of XGBoost trees are being used as best classifiers in these frameworks as well. XGBoost is also included for robust classification in order to optimize patches for the model, which includes multiple discriminant representations of patches. According to experimental results, the proposed method displays better results than the most advanced methods. It has been reported that Ting et al. [28] have presented an improved CNN model for the classification of breast cancer. The improved CNN model used in this study can be used to detect breast lesions, in terms of whether they are benign, malignant, or normal, with an accuracy of 90.5%, a sensitivity of 89.47%, a specificity of 90.71%, and a receiver operating characteristic of 0.901.

Rampun, et al. [29] concluded that ensemble deep learning is the most reliable method for predicting breast masses based on their appearance on mammograms. Accordingly, the Alex Net was modified to cater to the classification of breast masses. In the model selection process, the three best results are selected based on the highest validation accuracy. A prediction is then generated based on the average probability of the models. According to the results of the study, individual models have an accuracy range of 75% to 77%. Comparatively, an ensemble network provides a maximum accuracy of 80% based on its area under the curve. It has been found that the Chan-Vese level set method [30] is effective at extracting the contour of mammograms, and then using DL-CNNs, it can be learned features that are specific to the mammary mass and microcalcification clusters. At the final stage of the DL-CNN classification process, fully complex-valued relaxation networks are used to improve classification accuracy. This method has proven to be significantly more effective than traditional methods. The accuracy of the algorithm was 99%, its sensitivity was 0.9875, its specificity was 1.0, and its area under the curve (AUC) was 0.9815, allowing it to accurately identify normal, benign, and malignant mammograms. Combining CNNs and transfer learning, Lévy and Jain [31] developed a hybrid algorithm for diagnosing breast cancer using mammogram images. In order to overcome the inadequacy of the training data, preprocessing and augmentation were added. On the basis of the digital database for screening mammography (DDSM) dataset, they achieved more satisfactory results.

Using deep learning techniques, Hoteit et al. [32] proposed an improved method to classify mammograms. A CNN and VGG-16 algorithm were used to first classify the mammograms into mass and calcification. CNN was employed to classify mass and calcification into benign and malignant. After making modifications to each model, validation and testing accuracy were enhanced. To further reduce losses, additional modifications are required. The CNN model developed by Karatayev, et al. [6] was built up on histopathological images of invasive ductal carcinomas taken from the IDC dataset (containing histopathological images). It was found that the proposed model can correctly classify histopathological images by 92% using images of histopathological tissue. The study presented by Jadah, et al. [33] sought to estimate the categories of breast cancers with reliance on the convolutional neural network model AlexNet. This model will be used to diagnose breast cancer by applying a histopathological data set obtained from BreakHis images. Several parameters and data modifications are being applied in order to enhance the ability of the model to classify and recognize the image input. Up to 96% classification rate accuracy can be achieved with high training frequency and balanced data.

Using Local Binary Pattern (LBP) images as input, Madduri, et al. [34] proposed a CNN architecture and then compared its classification results with those of a standard CNN based on origin images. An automated classification scheme for cancer is proposed, which can be used to automatically categorize tumors into mild or moderate stages. This approach uses a 100-image dataset, 80% of which is used for training and 20% for testing. CNN architecture achieves 100% classification accuracy. It is shown in [35] that a light-weighted CNN can be constructed for predicting breast cancer based on an image dataset of breast mammography images. With the use of this model, it could be possible to diagnose mammary cancer even if a digital mammogram does not reveal any cancerous lesions that could indicate a cancerous condition. It seems that one of the greatest achievements of the proposed CNN is that based on the input mammography images, the input images can be classified as malignant or benign with an accuracy of 99.35%, which is the highest accuracy ever achieved for a large medical image dataset. There was a paper published by Li et al. [36] stating that they used feature-fusion convolutional neural networks to identify breast cancer-related images and classify them according to their features. A pair of convolutional neural networks, each pre-trained with a different structure, have been considered in this paper. In the process of fusing the features derived from both structures, the features are classified using a classifier. In terms of accuracy, this method classified breast cancer image datasets 89% accurately.

There are a number of differences between the aforementioned literatures in terms of their approach, dataset, number of images, and degree of accuracy, which is summarized in Table I.

TABLE I. RELATED LITERATURE IN ASSOCIATION WITH BREAST CANCER CLASSIFICATION USING CNN

Study	Year	Approach	Dataset	Number of Images	Accuracy
[20]	2022	CNN (VGG16 Architecture) with Type-3 Transformation	Wisconsin Original Breast Cancer (WBC) and Wisconsin Diagnostic Breast Cancer (WDBC) datasets from the UCI library. (Numerical Dataset)	WBC → 699 WDBC→ 569	WBC → 99.27% WDBC→ 100%
[21]	2023	CNN-LSTM	The Breast Cancer Histopathological Image Classification (BreakHis)	7909 microscopic images of breast tumor tissue	99% in binary classification (benign vs. malignant) and 92.50% for multi-class classifier in classifying subtypes of benign and malignant cancer
[22]	2023	CNN (ResNet50 Architecture)	BreakHis Dataset	9,109 samples of breast tumor tissue acquired from 82 cases	97%
[23]	2023	CNN Model	Breast histopathology section on the Kaggle online research community	65136 Breast cancer images	95%
[24]	2021	CNN Model	The dataset, Kaggle 162 H&E.	Around 277,524, 50 × 50 pixel RGB image patches.	87%
[25]	2021	(7-CNN model) Soft Voting Classifier	Hematoxylin–Eosin (H&E) Dataset	Total 58 patches	96.91%
[26]	2023	CNN (with Variational Autoencoder)	Breast histopathology images dataset	277,524 input images	73%
[27]	2022	CNN Model	A dataset from the BACH Grand Challenge	400 images of Hematoxylin and Eosin stained breast histology microscopy	86.50% patch level accuracy and 95% image level accuracy
[28]	2019	CNN Model	A digital mammogram database was prepared and provided by MIAS	Includes 322 originals (161 pairs)	90.5%
[29]	2018	CNN (AlexNet)	CBIS-DDSM Dataset	1593 mases	80%
[30]	2017	Level set + DL-CNN + FCRN (proposed CAD system)	Breast cancer dataset (MIAS and BCDR)	MIAS→ 322 images BCDR→ N/A	99%
[31]	2016	CNN (AlexNet, GoogLeNet)	The database for screening mammography managed collaboratively at University of South Florida (USF)	1820 images	AlexNet→89% GoogLeNet→92.9%
[32]	2022	Original CNN Model, and VGG16	(CBIS-DDSM) - Digital Database for Screening Mammography subset based on Breast imaging	3012 images	Original CNN→88% VGG16→90%
[6]	2021	CNN Model	Kaggle's IDC regular dataset (breast cancer histology images)	277,524 patches	92%
[33]	2022	CNN (AlexNet)	BreakHis (Breast Cancer Histopathology) dataset	7909 histopathology images	96%
[34]	2021	CNN architecture based on Local Binary Pattern (LBP) images	Histopathology images dataset from Kaggle	100	100%
[35]	2023	Light-weighted CNN	MIAS, DDSM, and INbreast dataset of breast mammography images	24576	99.35%

[36]	2021	CNN Model	Worked with the physical examination centers of related affiliated hospitals in order to collect data	145 ultrasound image samples of breast tumors	89%

IV. Discussion

With regards to the prior art presented in Table 1, it can be noted that each one of the CNN approaches had a slightly different structure in comparison to the other. In consequence, there was a difference in accuracy as a result of these factors, which varied with respect to the dataset, the number of images, etc. [37]. When the structure, the dataset, or the number of images in the dataset are changed, the accuracy will change as well. For example, Guleria et al. [26], the accuracy was approximately 73% when the input images were 277,524 images, as opposed to Madduri et al. [34], which had 100% accuracy when only 100 images were used. There is quite a substantial difference in the number of images generated by the two different CNN structures, regardless of which structure is used. Sharma and Kumar [20] on the other hand did not use images but converted numerical tabular data related to breast cancer into images and obtained various levels of accuracy based on these images. They obtained 99.27% accuracy in the case of breast cancer and 100% accuracy in the case of breast cancer, respectively, based on 699 and 569 images. A decrease in accuracy is generally observed with an increase in the number of images, i.e., the number of cases. However, it is important to note that this may not be the case for all structures, as shown in the work by Srikantamurthy et al. [21], based on 7909 microscopic images of breast tumor tissue that was used and an accuracy rate of 99% was achieved. It was CNN-LSTM that was used in their case. Furthermore, it has been noted in both Rampun et al. [29] and Jadah et al. [33] that the CNN (AlexNet) approach has been used with 96% accuracy when used with 7909 histopathology images and 80% accuracy when used with 1593 mases. As a result, despite the fact that the same method was employed in terms of the number of images, this wasn't the case in terms of the number of images. A similar conclusion can be drawn when using the same dataset as Alanazi et al. [24] and Kumar et al. [25], who both used Hematoxylin-Eosin (H&E) data sets and were able to obtain different accuracies based on the number of images used in their analysis. In fact, it is noteworthy that this contradiction occurs for the same dataset that has been reported by Ting et al. [28], Duraisamy and Emperumal [30], and Kaur, P. and Kaur, A. [35]. Based on the previous data, it can be concluded that there have been numerous research studies conducted in this field, which indicates the importance of this field in terms of research. Despite this, the level of contradiction remains high since the authors use different approaches, datasets, and images, which in turn results in high degrees of discrepancy in the accuracy of their results. Based on the findings of this study, a conclusion will be provided which comes to suggest some areas for improvement in the future based on the data collected. Yet, future research will will include fault diagnosis [38, 39], Internet of Things (IoTs) [40-42], and explainable AI (XAI) techniques [43] to enhance the outcome results. In addition to work on other diseases either in humans or plants [44, 45].

V. Conclusions

The disease of breast cancer affects millions of women worldwide. Detecting and classifying breast cancer early is essential for improving patient recoveries. Various medical image analysis tasks, including breast cancer classification, have been successfully performed using CNNs. The purpose of this paper is to provide an overview of the problem of breast cancer classification, and to demonstrate how CNN can be effectively utilized to solve it. There have also

1) The use of CNN in lung cancer diagnosis is of high Different CNN models leads to different effectiveness at detecting breast cancer, which affects its accuracy.
2) The accuracy in detecting breast cancer depends on different parameters such as the use CNN approach, the dataset, and the number of images.
3) A higher accuracy can be achieved by using a larger number of images, datasets, or even the CNN approach. However, this is won't be the case all the time.

Future research should be expanded on the accuracy of results based on an analysis of one parameter such as the CNN approach, the dataset, and the number of images. After the best accuracy is achieved in one chosen parameters, additional parameters may be added.

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