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Survey on Breast Cancer Disease Detection

Manish Yadav[1], Dr. Gourav Shrivastava[2]
Department of Advance Computing, School of Advance Computing, SAGE University, Bhopal[1,2]
manishyadav1000@gmail.com[1], gourav.s@sageuniversity.edu.in[2]

Abstract: *One of the leading causes of death for women in developing nations is breast cancer. For good results, early detection and treatment are essential. Breast cancer is thought to be the primary cause of death for women and arises from breast cells. There are two subtypes of this disease: ductal carcinoma in situ (DCIS) and invasive ductal carcinoma (IDC). More precise and dependable models for the diagnosis and treatment of this illness have been developed thanks to developments in artificial intelligence (AI) and machine learning (ML) methodologies. It's clear from the literature that using convolutional neural networks (CNNs) in conjunction with magnetic resonance imaging (MRI) can help prevent and detect breast cancer. Using the Breast Cancer dataset, this study looks at six different categorization models for breast cancer classification. The Python scikit-learn package is used for feature selection, and the Standard Scaler module is used for data processing.*

Keywords: *DCIS, Breast cancer, CNN, MRI, Python, feature selection.*

1. Introduction

The Breast Imaging Reporting and Database System score is abbreviated as BI-RADS. This is the method that radiologists use to put a number on a mammogram's results. In order to detect cancer, a mammography uses X-rays to examine the breasts. This is the most effective instrument for early detection of breast cancer. Medical professionals may use it as an additional diagnostic tool if they find suspicious lumps during a clinical breast examination. An accurate medical diagnosis of breast cancer cannot be provided by this test, however it may help in the discovery of anomalies. Keep in mind that unusual results may not necessarily mean cancer [18].

In order to carry out some medical procedures correctly, medical imaging is required, which in turn requires the processing and display of massive amounts of data. Recent developments in deep learning algorithms have brought a lot of interest to the topic of research and led to noticeable improvements in accuracy. It is standard practice in radiology to use medical image analysis to detect and grade different kinds of abnormalities in X-ray pictures, determine if the pictures show healthy or diseased states, and so on.

The healthcare system adopted computer-aided detection (CAD) systems in the 1980s, despite the presence of multiple false positives [30]. Unlike conventional image processing, which tends to prioritize improving the visual appeal or creative expression of the output, the main goal of medical image processing is to make the content more readable.

Improving the visual representation to make certain features more noticeable and automatically retrieving pertinent data is one possible strategy [30]. By carefully examining each patient's medical imaging, radiologists must first and foremost determine a differential diagnosis. Examining the presence or absence of a medical disease and determining the exact type of cancer are both part of this procedure [31]. Medical personnel spend a great deal of time and energy on the difficult task of analyzing medical images. In an effort to reduce the burden on doctors and free up their time for other duties, the computer-aided diagnosis (CAD) system was created in 1980[30] to evaluate medical images. However, compared to human medical experts, the computer-aided design (CAD) technology used back then produced more false positive outcomes. Unnecessary biopsies and longer evaluation durations were the results [31]. The use of medical images for tasks including better picture capture, illness detection, treatment, and prediction has developed and improved because to advancements in computer vision. Many factors, including shape, texture, contour, previous occurrences, and contextual information collected from a series of photographs, can be included in 3D and 4D data, which could improve human understanding. Significant improvements in diagnostic and treatment results were achieved by the automated interpretation of three-dimensional medical pictures. New questions in robotics, computer vision, and graphics are spawned by this automation. It is critical to collect a large number of diagnosed samples to ensure a well-tested hypothesis.

2. Literature Review

Radiologists need specialized training and experience to detect breast cancer using magnetic resonance imaging (MRI). Longer wait times and later diagnoses are the results of radiologists working longer hours to meet the growing demand for breast MRIs and the overall lack of radiologists [6,7]. Radiologists' capacity to understand breast MRI pictures, clinical decision-making, and patient outcomes can all be enhanced with the use of machine learning [10, 11]. Large magnetic resonance imaging (MRI) datasets can be used to train machine learning algorithms to identify and categorize potentially problematic areas [11, 12]. With any luck, this will lead to more accurate diagnoses with fewer false positives and negatives. Several studies have demonstrated that machine learning has the potential to surpass doctors in identifying breast cancer through MRI scans [13].

Classification of breast cancer from mammography images using a framework based on convolutional neural networks (CNNs). Prior to viewing, the mammography images needed to undergo preprocessing. A deep learning model trained on the preprocessed photos was used to extract the features. Following the collection of attributes from the last layer, a convolutional neural network classifier known as Softmax was employed for their classification. With the suggested model, the mammography image categorization in the presented framework became more accurate. In comparison to the state-of-the-art alternatives, the suggested framework outperforms them with accuracy values of 0.8585 and 0.8271 [4]. Preliminary results from a study that employed transfer learning to identify breast abnormalities with a high cancer risk were reported in [32]. A plethora of deep learning models were ultimately assessed. After much trial and error, they determined that ResNet50 and MobileNet were the best deep learning models. Achieving 78.4% and 74.3% accuracy, respectively, were the best levels reached by both models. The accuracy of the categorization was further enhanced by employing a range of preprocessing techniques. Finally, a novel hybrid processing approach combining PCA and RV was presented by researchers in [33]. Based on diffusion-weighted magnetic resonance (DCE-MR) images, Li et al. [29] distinguished between benign and malignant tumors in 143 patients using 3D convolutional neural networks (CNNs). Every set of MR images had their enhancement ratios determined, and ROIs and VOOs were identified for both 2D and 3D DCE-MRI. When comparing the 2D and 3D CNNs, the 3D CNN has a better area under the curve (0.801 vs. 0.739). Additionally, the 3D CNN performed better than the 2D model with sensitivity = 0.781, specificity = 0.744, and accuracy = 0.823. By including more information, the DCE-MRI enhancement maps made breast cancer diagnoses more accurate. With such high values, the results show that 3D CNN can be used to detect breast cancer in MR images and reduce the requirement for human feature extraction. One hundred high-risk female patients with 68 malignant and 32 benign lesions segmented by two skilled radiologists were subjected to Knowledge-Driven Feature Learning and Integration (KFLI) on their DWI and DCE-MRI data. Thanks to Feng et al. [23], we have this data. A reported accuracy rate of 0.85 was used. Two modules—one for adaptive weighting and one for sequence division—were built into the model. Cooperation in diagnosis is enhanced by the adaptive weighting module's automatic feature integration. A sequence division module that takes lesion characteristics into account is proposed for feature learning. In addition to providing the sub-sequence contribution, this method instructs radiologists to zero in on sequences linked to characteristics that substantially impact lesion diagnosis. Radiologists will be able to save time and better comprehend the deep network output because of this. With the use of CNN, Marrone et al. [31] assessed 42 females, 25 of whom had benign tumors and 42 of whom had malignant ones. An expert radiologist obtained the ROIs and performed the manual segmentation. A degree of precision as high as 0.76 was reached. While pre-trained AlexNet fine-tuned by removing the last learned layer yielded an area under the curve (AUC) of 0.73, pre-trained AlexNet without fine-tuning reached 0.76. The second approach might reduce the number of training photos required. Once the last internal CNN layer has been highlighted using AlexNet pre-trained on the ImageNet database, the preparing-from-scratch AlexNet model is complete. In this fresh supervised training, the accuracy was 0.55 and the AUC was 0.68.

3. Conclusion

Artificial intelligence has the potential to completely change the way that breast cancer is screened for and diagnosed. By assisting radiologists in becoming more accurate and efficient, artificial intelligence could ultimately improve patient outcomes. Additionally, it may lessen the need for pointless testing and treatment, such as biopsies. But there are certain obstacles that have prevented widespread use in clinical practice thus far. Large, varied, and thoroughly annotated images that are easily accessible for research are required. The outcomes of deep learning must be more precise, comprehensible, elidable, and broadly applicable. Subsequent study might include more clinical data and risk variables, such as age, family history, or genetic abnormalities, into the model to improve diagnosis accuracy and enable individualized medication.

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