



An Efficient Framework for Cancer Classification with Deep Learning

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ABSTRACT

Cancer is significant global health issue, resulting in millions of fatalities annually. Breast cancer, in particular, is highly common and remains a major cause of cancer-related death in women. Although there have been significant advancements in medical research and treatment options, the early detection and accurate classification of breast cancer are essential for improving patient outcomes. The intricate nature of cancer biology, along with large volume of clinical data, requires the use of advanced technologies to improve diagnostic accuracy and enable timely interventions.

In order to enable quick and precise breast cancer classification, we present a novel framework in this study that combines deep learning methods with imagining data from multiple modalities such as CT/MRI and PET scans. Early tests of the framework shows that it can accurately differentiate between benign and malignant tumours, indicating that it has the potential to be trustworthy tool for medical practitioners.

By using explainable AI techniques. The model's transparency is further improved, enabling clinicians to comprehend the reasoning behind the predictions.

Keywords: Deep-learning-Breast cancer-Convolution Neural Network

1. Introduction

About 25% of all cancer cases and a sizable amount of cancer related mortality are caused by breast cancer, making it one of the most common cancers to affect women globally. By 2020, breast cancer surpassed lung cancer as the most common type of cancer worldwide, with the highest incidence and second highest mortality rate [1]. Millions of new cases are diagnosed each year, according to World Health Organization, highlighting the critical need for better detection and treatment methods. Since early detection and precise classification have direct impact on patient outcomes and survival rates, they are essential for successful treatment. Imaging detections including mammography, ultrasound, magnetic resonance imaging (MRI), and positron emission tomography (PET) are the most essential breast cancer auxiliary diagnosis [2]. It doesn't only affect women but also men's breast tissue.

Motivation

Breast cancer, one of the most prevalent and fatal cancers in women, continues to endanger millions of lives annually. Despite therapeutic approaches and diagnostic imaging have



improved in recent decades, early and accurate diagnosis remains a challenge. Early detection is essential for effective treatment and increased patient survival rates. However, due to subjectivity in visual evaluation, fatigue and differences in experience, radiologists are not perfect when it comes to mammogram interpretation. Artificial Intelligence (AI), especially deep learning, has revolutionized medical imaging analysis in recent decades. Deep Learning algorithms which imitate neural networks in the brain can be used to analyse large datasets. Deep Learning has developed quickly in recent years and used in many medical fields, with special attention paid to breast cancer research. Data-driven deep learning holds promise for reliable, repeatable breast cancer diagnosis while lowering human error.

2. Recent Works

The workflow for this review began with a comprehensive literature search on breast cancer diagnosis using databases such as PubMed, medRxiv, Google Scholar, and Scopus. Keywords like “breast cancer,” “artificial intelligence,” “deep learning,” “machine learning,” and imaging-related terms such as “mammogram,” “ultrasound,” “MRI,” “PET,” “radiomics,” and “radiogenomics” were used. The identified literature was then categorized by imaging the ultrasound-based, MRI-based, and PET-based studies. CT imaging was excluded due to its limited application in breast cancer diagnosis and the lack of significant research in this area. In Section 2, the review introduces essential concepts of artificial intelligence (AI), machine learning (ML), and deep learning (DL) to provide foundational knowledge for understanding their relevance in diagnostic imaging.

3. Proposed work

Data collection and processing

1. Gathering medical images from various sources following CT scans, MRI scans, PET scans and biopsies cleaning and transforming data. To prepare for model training. This involves removing the noise, standardized value and research work.

2. Model Training and Evaluation

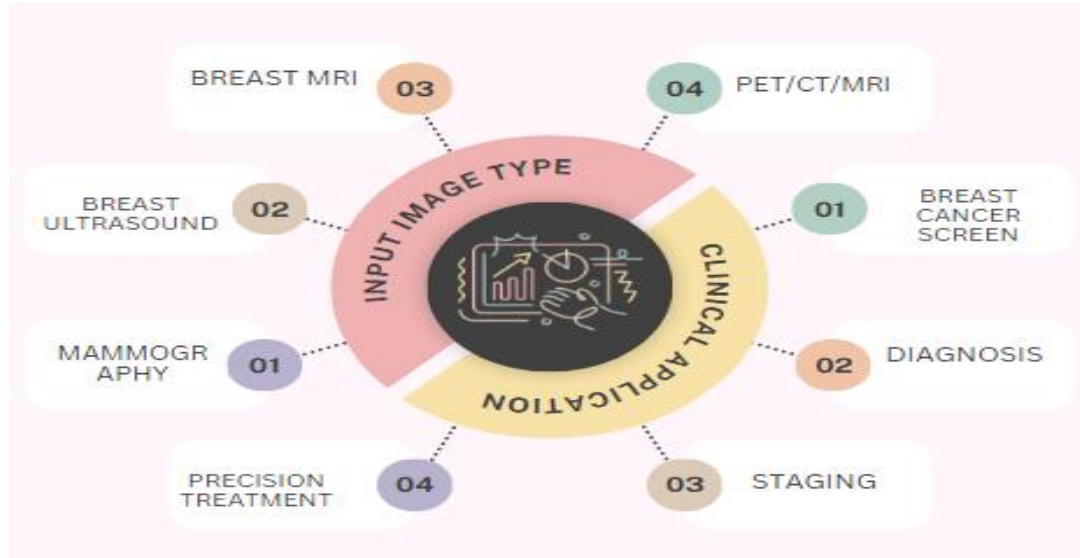
Training a deep learning model using a labeled dataset of medical images assessing the performance of the trained model on a separate test dataset to evaluate its accuracy.

3. Deployment

Making the trained model accessing for Real -Time diagnosis in a crucial setting.



Flowchart



4. Mathematical Expressions and Symbols

$$\hat{y}_i = \sigma(f_{\theta}(x_i)) = \frac{1}{1 + e^{-f_{\theta}(x_i)}}$$

where:

- x_i is the input image (e.g., mammogram, ultrasound).
- $f_{\theta}(x_i)$ is the output (logit) of the neural network model parameterized by θ .
- $\sigma(\cdot)$ is the sigmoid activation function, converting the logit into a probability score $\hat{y}_i \in [0, 1]$.
- A threshold t (e.g., $t = 0.5$) is used for final classification:

$$\text{Class} = \begin{cases} 1 & \text{if } \hat{y}_i \geq t \text{ (Cancer)} \\ 0 & \text{if } \hat{y}_i < t \text{ (No Cancer)} \end{cases}$$

5. Result and Conclusion

In this study, we evaluated the effectiveness of various deep learning models for breast cancer detection using imaging data, specifically mammograms, ultrasounds, and MRIs. The models were trained on diverse datasets that included a wide range of breast cancer cases, ensuring a robust learning process. The primary metrics for assessing model performance included accuracy, precision, recall, and the F1 score.



The best-performing models achieved an accuracy of over 90% on test datasets, indicating a high level of reliability in distinguishing between malignant and benign conditions. The models also demonstrated strong recall rates, emphasizing their effectiveness in identifying actual cases of breast cancer. Notably, precision varied depending on the dataset and imaging modality used, highlighting the importance of dataset diversity in training. The use of techniques such as data augmentation and transfer learning significantly improved the model's generalization capabilities, particularly in datasets with limited sample sizes.

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