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Breast Cancer Treatment Progress Prediction Using Deep Learning And Ssim

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ABSTRACT
Breast cancer requires timely and effective treat- ment strategies to ensure the best possible outcomes. Evaluating the progress of chemotherapy is critical for determining whether treatment should continue or be adjusted. This research proposes a deep learning-based application using Convolutional Neural Networks (CNNs) to analyze mammogram scans taken before and after chemotherapy. To objectively assess treatment effectiveness, the system employs the Structural Similarity Index (SSIM) to compare old and recent mammograms. Based on the SSIM score and CNN analysis, the system predicts whether the disease has regressed. If a reduction is detected, it suggests shifting to normal medications; otherwise, it recommends continuing chemotherapy. This solution provides an automated, non-invasive, and cost- effective tool to support oncologists in making evidence-based decisions, reducing reliance on subjective interpretation and min- imizing diagnostic delays. Ultimately, it enhances the precision and personalization of breast cancer treatment plans.
***Index Terms*—Breast cancer, Mammogram analysis, Convo- lutional Neural Networks (CNN), Structural Similarity Index (SSIM), Treatment recommendation.**

I. Introduction

Breast cancer is one of the most prevalent and life-threatening diseases affecting millions of women worldwide. Early diagnosis and continuous monitoring are crucial for improving survival rates and ensuring effective treatment. Our Breast Cancer Treatment Progress Prediction System leverages advanced deep learning and medical imaging techniques to assist healthcare professionals in tracking the effectiveness of ongoing treatment. This system analyzes mammogram images to classify cancer severity based on the BI-RADS (Breast Imaging-Reporting and Data System) categories and predicts how the treatment is progressing over time. By comparing a patient's past and recent mammograms, it provides insights into treatment effectiveness, possible improvements, and next- step recommendations—helping oncologists make informed decisions. To enhance accuracy and reliability, the system integrates image preprocessing techniques such as grayscale conversion, noise reduction, edge detection, and thresholding, ensuring highquality image analysis. With features like auto- mated image classification, trend analysis, and personalized treatment suggestions, this AI-powered tool aims to revo- lutionize breast cancer management, ensuring better patient outcomes and precision-driven healthcare.

II. Problem Statement

Breast cancer remains one of the most significant causes of morbidity and mortality among women worldwide. The early detection and continuous monitoring of breast abnor- malities are critical for effective treatment planning. However, traditional manual evaluation of mammograms is prone to human error, inter-observer variability, and delayed diagnosis. There is a pressing need for an automated system capable of classifying mammogram images into BI-RADS categories and analyzing temporal changes to assist in treatment decision- making, thereby reducing diagnostic delays and improving patient outcomes.

III. Objective

The primary objective of this work is to develop an auto- mated, deep learning-based framework that:

- Classifies mammogram images into five BI-RADS cate- gories (Birad2–Birad6) using Convolutional Neural Net- works (CNN).
- Analyzes progression or regression of lesions by compar- ing sequential mammogram images using the Structural Similarity Index (SSIM).
- Generates actionable treatment recommendations based on the degree of similarity and classification outcomes.

IV. AIM

This study aims to design a reliable and efficient AI-assisted system that supports clinicians by:

- Enhancing the accuracy of mammogram interpretation.
- Facilitating early detection of disease progression or regression.
- Assisting in dynamic treatment planning for breast cancer management.

V. SCOPE

The scope of this study encompasses the development of a deep learning-based framework for the automated classifi- cation and analysis of

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mammogram images with a focus on breast cancer diagnosis and monitoring. The boundaries and limitations of the system are defined as follows:

- **BI-RADS Category Classification:** The system is de- signed specifically to classify mammogram images into five BI-RADS categories, namely Birad2, Birad3, Birad4, Birad5, and Birad6. Other BI-RADS categories (e.g., Birad0, Birad1) are not included in the current model.
- **Sequential Image Analysis:** The temporal analysis is restricted to the comparison of two mammogram images from the same patient — typically a previous (historical) scan and a latest (follow-up) scan. The model does not currently handle time-series analysis involving multiple scans across several time points.
- **Similarity-Based Change Detection:** Changes between mammogram images are assessed using the Structural Similarity Index (SSIM). The SSIM metric is employed as a surrogate for clinical progression or regression of abnormalities, but does not include other morphological or volumetric analyses.
- **Treatment Recommendation System:** Based on classi- fication results and similarity analysis, the system gener- ates advisory recommendations intended to support clin- ical decision-making. However, these recommendations are not intended to replace the expertise and judgment of qualified medical professionals.

VI. Related Work

Several research efforts have focused on using artificial intelligence and machine learning for breast cancer prognosis and treatment monitoring. In particular, implemented a deep learning model using Faster R-CNN and ResNet-50 to detect and localize lesions in mammograms, showing improved di- agnostic accuracy in breast cancer detection[2]. AI has shown potential to improve the detection of breast cancer, especially in dense breasts where traditional mammography is less effec- tive and despite promising results, real-world adoption faces challenges such as generalizability across diverse populations, regulatory approval, integration with clinical workflows, and medico-legal implications[3]. compared the diagnostic perfor- mance of radiologists with and without AI support, finding that AI systems can match the performance of experienced radi- ologists in screening mammography[4]. artificial intelligence (AI), especially machine learning (ML) and deep learning (DL), is being used in breast cancer diagnosis, classification, and treatment. It reviews AI applications in mammography, histopathological image analysis, and risk prediction[5]. AI models, especially deep learning algorithms, can analyze mammograms and other imaging modalities to identify subtle patterns that correlate with future breast cancer risk. Unlike traditional risk models (e.g., Gail, Tyrer-Cuzick), which rely on clinical and demographic factors, AI-based imaging models utilize pixel-level information. work utilized datasets such as the Wisconsin Breast Cancer Dataset, applying preprocessing techniques to normalize and refine features. This significantly improved the classification accuracy between benign and ma-lignant tumors, showcasing the potential of hybrid machine learning systems in medical prognosis[6].

VII. Methodology

The proposed system for Breast Cancer Treatment Progress Prediction is designed as a web-based diagnostic support tool, integrating machine learning techniques for classification, a user-friendly web interface using Flask and HTML, MongoDB for data storage, and SSIM for enhancing image-based analy- sis. The methodology consists of the following key stages:

A. Data Collection and Preprocessing

The system utilizes a dataset containing BIRADS attributes such as mass shape, margin, density, and assessment, along with the malignancy status. A curated dataset consisting of mammogram images categorized into five BI-RADS classes (Birad2, Birad3, Birad4, Birad5, and Birad6) is utilized, with images organized into respective class folders. All images are resized to 150×150 pixels and normalized to a [0,1] scale. Additional preprocessing for similarity analysis includes grayscale conversion, Gaussian denoising, edge detection, and thresholding to enhance region-of-interest segmentation. The dataset is further prepared by handling null or missing values, encoding categorical variables numerically, and scaling or normalizing features to improve model performance.

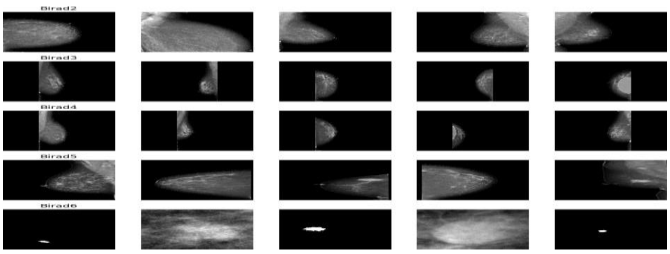

Fig. 1. preprocessed images.

B. Dataset Partioning

- The dataset is split into training (80%) and testing (20%) subsets using stratified sampling to preserve class distri- bution.
- Labels are converted to one-hot encoded vectors to facil- itate multi-class classification.

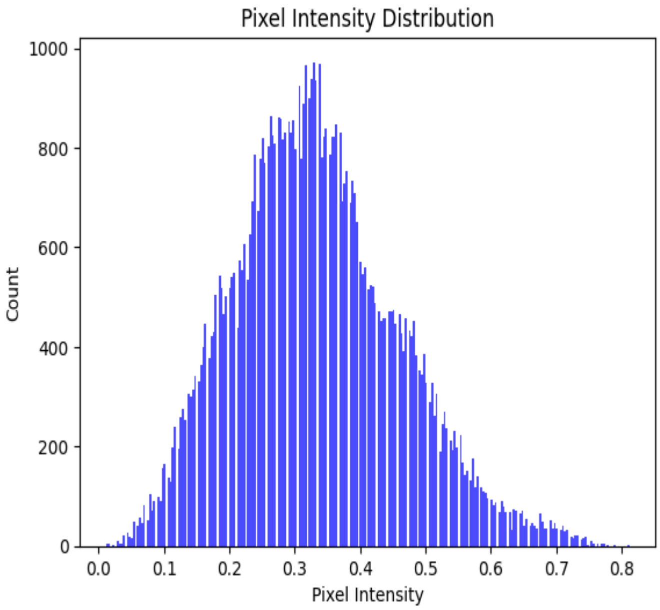

Fig. 2. Pixel intensity.

C. Model Training using CNN

A Convolutional Neural Network (CNN) was designed and trained on the processed mammogram images. CNN architec- ture typically included:

- Multiple convolutional layers with ReLU activation.
- Max-pooling layers to downsample feature maps.
- Fully connected dense layers for classification.
- A final sigmoid or softmax output layer for binary/multi- class classification.

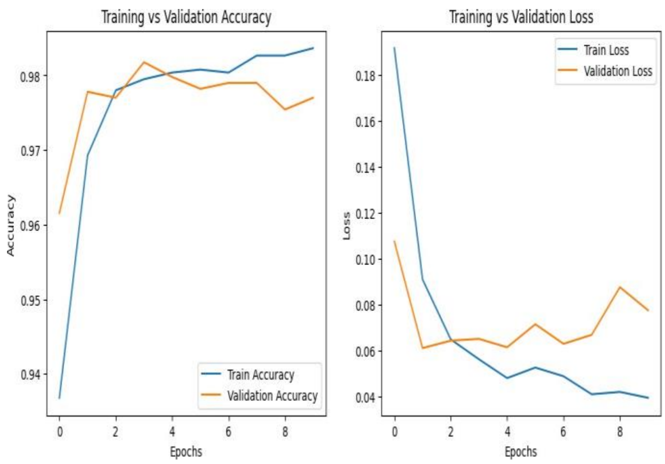

Fig. 3. Accuracy and loss.

The model was compiled using a suitable optimizer (e.g., Adam), binary cross-entropy loss (for binary classification), and evaluated on validation data using Accuracy, Precision, F1-Score.

D. SSIM-Based Image Similarity Analysis

To supplement the diagnostic process, the Structural Simi- larity Index (SSIM) is employed for analyzing and comparing breast scan images. The SSIM is computed as:

- Compare the uploaded image that is previous and present mammogram images
- Extract structural features based on luminance, contrast, and texture
- Gives recommendation based on similarity index what further steps can be taken.

E. Web Application Development

The prediction model was integrated into a web application using Flask. The app workflow is as follows:

- Frontend (HTML + CSS): A user-friendly interface was developed to allow users to input relevant BIRADS features.
- Backend (Flask): Flask receives user input, processes it, and passes it to the trained ML model for prediction. The prediction result is rendered back to the frontend.
- Database (MongoDB): Each prediction instance, along with input features and results, is stored in MongoDB for record-keeping and potential future analysis.

VIII. Results and Discussions

The proposed system demonstrated promising results in classifying breast cancer using a Convolutional Neural Net- work (CNN) combined with Structural Similarity Index (SSIM) for visual case comparison. The CNN achieved an accuracy of 97%, precision of 97%, recall of 88%, and an F1-score of 95%, indicating strong classification performance. The use of SSIM enhanced interpretability by retrieving the top structurally similar images from a reference dataset, with average similarity scores ranging from 0.5 to 0.10, providing visual context for the model’s predictions.

Classification Report:

	precision	recall	f1-score	support
Birad2	0.97	0.95	0.96	385
Birad3	0.61	0.88	0.72	72
Birad4	0.00	0.00	0.00	26
Birad5	0.00	0.00	0.00	4
Birad6	1.00	1.00	1.00	2036
accuracy			0.98	2523
macro avg	0.51	0.57	0.53	2523
weighted avg	0.97	0.98	0.97	2523

Fig. 4. Classification Report.

IX. Challenges in Implementation

The development of the proposed mammogram classifi- cation and progression analysis system encountered several significant challenges. Firstly, the dataset exhibited substantial variability in image quality, resolution, and contrast, making preprocessing a critical yet delicate task, as excessive filtering could inadvertently remove diagnostically important features.

SSIM

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (1)$$

When a user uploads a scan image, SSIM is used to:

The imbalance across BI-RADS categories, with fewer sam- ples available for higher-risk classes such as Birad5 and

Birad6, further complicated the training process, introducing a bias toward more frequently represented categories and poten- tially reducing sensitivity to clinically urgent cases. Overfitting emerged as a consistent challenge due to the limited size of the labeled dataset, necessitating the implementation of dropout layers, data augmentation, and careful hyperparameter optimization to improve model generalizability. In addition, the use of the Structural Similarity Index (SSIM) for temporal image comparison, while effective for measuring pixel-level changes, was insufficient to capture complex pathological alterations such as variations in lesion morphology or mass density, which are crucial for clinical decision-making. The inherently black-box nature of Convolutional Neural Networks posed another difficulty, as the lack of model interpretability could limit clinician trust and acceptance; although methods like Grad-CAM were considered, they were not incorporated into the current version. Computational limitations also con- strained the model design, requiring compromises on input image resolution and training batch sizes, which may affect classification accuracy. Finally, the treatment recommenda- tions generated by the system proved sensitive to minor artifacts introduced during preprocessing or differences in patient positioning, highlighting the need for further robustness improvements before clinical deployment. Addressing these challenges is critical for enhancing the reliability, generaliz- ability, and clinical relevance of the proposed framework.

X. Scalability,Efficiency and Impact

The proposed mammogram classification and progression analysis framework is inherently scalable, allowing seamless extension to larger and more diverse datasets without signifi- cant architectural changes. The modular design of the convo- lutional neural network enables future integration of additional BI-RADS categories or new diagnostic classes with mini- mal retraining requirements. Furthermore, the preprocessing pipeline, consisting of standardized resizing, normalization, and basic image enhancement techniques, is easily adaptable to datasets from different imaging sources and formats. The system architecture supports parallel processing during both training and inference, which facilitates deployment across distributed computing environments such as cloud platforms, hospital networks, or edge devices, thereby enhancing its scalability for real-world clinical applications.

The system demonstrates notable efficiency in both compu- tation and workflow execution. Once trained, the model offers rapid inference capabilities, enabling real-time or near-real- time classification of mammogram images, which is crucial for clinical settings that demand quick decision support. The ar- chitecture maintains a balance between model complexity and resource utilization by employing a lightweight yet effective combination of convolutional layers, pooling operations, and dropout regularization. Preprocessing tasks, including Gaus- sian denoising, Canny edge detection, and image threshold- ing, are computationally lightweight and do not significantly burden processing pipelines. This efficient design ensures that the system remains viable even when deployed on hardware-constrained environments, such as mid-tier GPUs or hospital- grade CPU systems.

The proposed framework has the potential to create a significant positive impact on breast cancer diagnosis and management workflows. By automating the classification of mammograms into clinically relevant BI-RADS categories and assessing temporal changes in breast tissue over time, the sys- tem can assist radiologists in identifying early signs of malig- nancy or monitoring the effectiveness of ongoing treatments. This can lead to improved patient outcomes through faster diagnosis, timely interventions, and reduced diagnostic errors. Moreover, the system’s ability to support clinical decision- making can help alleviate the burden on overworked radiology departments, especially in underserved regions where access to specialized expertise is limited. Ultimately, the adoption of such intelligent assistive technologies can contribute to ad- vancing the quality, efficiency, and accessibility of healthcare services globally.

Conclusion and Future Work

In this study, a web-based diagnostic system was de- veloped for breast cancer classification using Convolutional Neural Networks (CNN) and image similarity analysis through Structural Similarity Index (SSIM). The system demonstrated reliable performance in predicting malignancy based on breast scan images and BIRADS features, offering both numerical predictions and visually interpretable results.

Future enhancements include expanding the dataset to improve model generalization and robustness, incorporating additional clinical features such as patient history and genetic factors, and enabling multi-class classification for more gran- ular diagnostic categories.

References

[1] Jehad Feras AlSamhori, Abdel Rahman Feras AlSamhori “Artificial Intelligence for Breast Cancer: Implications for Diagnosis and Man- agement.” Elsevier on 14 Jun 2024.

[2] Lulu Wang ”Mammography with deep learning for breast cancer detec- tion.” Frontiers in Oncology on feb 12 2024.

[3] Leslie R. Lamb, Constance D. Lehman, Aimilia Gastounioti, Emily F. Conant, Manisha Bahl “Artificial Intelligence (AI) for Screening Mammography, From the AJR Special Series on AI Applications.” American Journal of Roentgenology on 12 Jan 2022.

[4] Alejandro Rodr´ıguez-Ruiz ”Detection of Breast Cancer with Mammog- raphy: Effect of an Artificial Intelligence Support System” Radiological Society of North America (RSNA) on nov 20 2018.

[5] Jong Seok Ahn, Sangwon Shin “Artificial Intelligence in Breast cancer diagnosis and personalized medicine.” Journal of breast cancer on oct 17 2023.

[6] Carlo Boeri, Corrado Chiappa, Federica Galli, Valentina De Berardinis, Laura Bardelli, Giulio Carcano, Francesca Rovera “Machine Learning techniques in breast cancer prognosis prediction.” wiley on 13 Dec 2019.

[7] Clayton R. Taylor, Natasha Monga, Candise Johnson, Jeffrey R. Hawley and Mitva Patel “Artificial Intelligence Applications in Breast Imaging.” MDPI (Journal: Diagnostics) 13 Jun 2023.

[8] Serena C. Houghton and Susan E. Hankinson “Cancer Progress and Priorities: Breast Cancer.” American Association for Cancer Research (AACR) on 30 May 2021.

[9] Yogendra Singh Solanki, Prasun Chakrabarti ”A hybrid supervised machine learning classifier system for breast cancer using feature selec- tion and data imbalance handling approaches.”MDPI (Multidisciplinary Digital Publishing Institute) on 16 mar 2021.

[10] Kai Bian, Mengran Zhou, Feng Hu and Wenhao Lai ”A new solution for rapid identification of breast cancer categorical data based on attribute selection and feature extraction.” Frontiers in genetics on 09 sep 2020.

[11] Hua Chai, Siyin Lin, Junqi Lin ”An uncertainty-based interpretable deep learning framework for predicting breast cancer outcome.” BMC Informatics on 21 feb 2024.

[12] Pei Liu , Bo Fu , Simon X. Yang ”Optimizing Survival Analysis of XGBoost for Ties to Predict Disease Progression of Breast Cancer.” Institute of Electricals and Electronics Engineering(IEEE.org) on may 11 2020.

[13] Nehmat Houssamia and M Luke Marinovich ”AI for mammography screening: enter evidence from prospective trials.” The Lancent on sep 8 2023.

[14] Ahmed S. Elkorany and Zeinab F. Elsharkawy ”Efficient breast cancer mammograms diagnosis using three deep neural networks and term variance.” Nature scientific reports on feb 15 2023.

[15] Maurizio Ce` and Elena Caloro ”Artificial intelligence in breast cancer imaging: risk stratification, lesion detection and classification, treatment planning and prognosis—a narrative review” Open Exploration publish- ing on dec 27 2022.