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Comparative Study of Deep Learning Based Model Approach for Early Breast Cancer Detection

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Abstract— In cancer Breast cancer is indeed one of the most common cancers globally and a leading cause of cancer related deaths, though it primarily affects women. It is the most common cancer among women and the second most common overall, after lung cancer. In men, breast cancer is much rarer but still a serious concern, with significantly lower incidence rates compared to women. Early detection and advances in treatment have improved survival rates over the years. Breast cancer represents about 30% of all new cases diagnosed in women each year. According to the American Cancer Society's 2024 estimates, there will be approximately 310,720 new cases of invasive breast cancer and 56,500cases of ductal carcinoma in situ (DCIS) diagnosed [1]. Early detection is crucial in improving outcomes for breast cancer. Today's emerged AI and deep learning techniques can also improve both accuracy and the effectiveness of treatment and gives better outputs. This paper represents the comparative study of deep learning-based CNN architectures for breast cancer detection with CBIS-DDSM Mammogram Dataset.

Keywords*—Breast Cancer Detection, Mammogram imaging, Deep learning, CNN, VGG16, ResNet50, CBIS-DDSM, Classification*

I. INTRODUCTION

Breast cancer remains a leading cause of cancer related morbidity and mortality worldwide, highlighting the advancement and advanced technique for early detection of breast cancer In recent years, artificial intelligence AI, specifically a deep learning technique like VGG16, has shown promising potential to augment breast cancer detection efforts. In 2024,an estimated 43,600 women in the United States are expected to lose their lives to this disease. Based on the report of American Cancer Society, an estimated 281,550 new cases of breast cancer are projected for 2024 in the United States alone, with an additional 49,290 cases of ductal carcinoma in situ (DCIS) expected. This underscores the urgency to improve diagnostic accuracy and early detection strategies.

Deep learning is a emerged as a promising technique for detecting breast cancer, utilizing advanced artificial intelligence techniques to analyze medical imaging data accurately and efficiently. Convolution neural networks (CNNs) such as VGG16 and other sophisticated models excelin identifying intricate patterns and abnormalities in mammograms and other breast imaging modalities. This technology aims to enhance early detection rates, minimize false positives, and improve overall patient outcomes by equipping radiologists and clinicians with precise diagnostic and treatment planning tools. Ongoing research in deep learning for breast cancer detection show significant potentialto advance medical diagnostics and enhance healthcare outcomes on a global scale. VGG16, a robust convolution neural network originally designed for general image recognition tasks, has been adapted then fine-tuned for medical imaging applications, including breast cancer detection. Its deep layers enable it to learn intricate patterns and features from mammograms and other medical images, potentially enhancing the identification of subtle abnormalities indicative of cancerous lesions. Mammography continues to be the cornerstone of early detection for breast cancer, recommended as a routine screening starting at age 40 for women of average risk. This

practice aims to detect potential abnormalities early, improving the chances of successful treatment and outcomes.

This introduction sets the stage for exploring how Deep learning, through models like VGG16, aims to bolster early breast cancer detection. By leveraging its capabilities to analyze complex visual data, researchers and healthcare professionals aspire to reduce false positives, improve diagnostic precision, and ultimately advance patient outcomes in the ongoing battle against breast cancer.

A. Related work

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In the realm of mammography-based breast cancer diagnosis,there has been a burgeoning interest in leveraging computer- aided detection (CAD) systems to enhance diagnostic precision. These systems employ algorithms to scrutinize mammography images, pinpointing suspicious regions that may signify the presence of breast cancer. At starting stage, CAD based systems relied on hand-crafted features and basicclassifiers such as SVM and decision trees [2][9][11]. However, their accuracy was constrained by the quality of these manually engineered features and the simplicity of the classifiers. Cognition and image segmentation have demonstrated promising outcomes in mammography-based breast cancer detection. Additionally, techniques like transferlearning, which involves fine-tuning pre-trained deep learning models. In recent years, the advent of deep learning has catalyzed a shift towards employing convolution neural networks (CNNs) for CAD in mammography. Previous research reference of [2][4][8][10] introduced CNN models, it renowned for their efficacy in various computer vision tasks such as object relearning models on specific datasets, and multi-modal learning, which integrates data from multiple sources such as mammograms and patient information [2], have further enhanced the performance of CAD systems. Reference[11] they "introduced performance of four classification algorithms—decision tree, support vector machine (SVM), convolutional neural network (CNN), and logistic regression—using the Wisconsin Breast Cancer dataset (WBCD). To ensure robust evaluation, they employed k-fold cross-validation to validate prediction accuracy and fine-tune model hyperparameters." Among the models tested, the CNN demonstrated the highest accuracy, achieving 98%. Additionally, employing an ensemble model further enhanced accuracy to 96%, surpassing the average accuracy of the base models, which was 94%. These findings underscore the efficacy of CNN and ensemble techniques in improving predictive performance on the WBCD dataset.

Reference [1][10] aims to leverage VGG16, "a pre-trained convolutional neural network (CNN) model, to extract high- level features from breast histopathological images." By utilizing VGG16, renowned for its deep learning capabilities, we seek to enhance the diagnostic process and improve the effectiveness of analyzing these images.

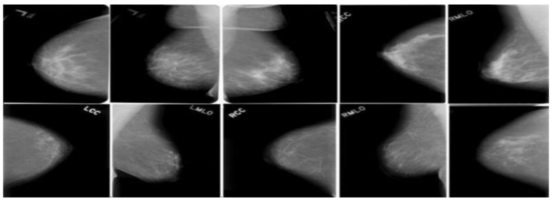


Figure 1: Breast Mammography images from CBIS-DDSM dataset. DDSM database comprises 2,620 scanned film mammography, encompassing cases classified into two class benign, and malignant categories, each accompanied by verified pathology information, images include their class label for multiclass task [16].

II. MATHODOLOGY

A: DATASET: The Curated Breast Imaging subset of DDMS represent a standard version of Digital Dataset of mammogram Imaging. Originally compressed 2620 mammogram Imaging studies the DDSM includes case classified and pathological verified details, categorized into normal, benign and malignant. This classified data set serveas an important resource to develop this model.

The CBIS-DDSM collection is a trimmed subset of DDSM data meticulously curated by mammography. It features images that have been decompressed and converted into DICOM format, achieved by updated region of interest (ROI), segmentation, bounding boxes, and pathological diagnoses for training purposes.

B: Model Selection: CNNs Convolution Neural Networks, area prominent deep learning technique characterized by their interconnected structure. They are widely utilized across various domains including image classification recently, in medical field imaging such as breast cancer diagnosis. A typical CNN comprises three fundamental layers: convolution layers, pooling layers, and fully connected layers. These layers are stacked sequentially to construct a deep architecture capable of automatically extracting meaningful features from raw data., a CNN, which is pivotal in tasks such as image classification, object detection, and medical image analysis. CNNs excel at automatic feature extraction and hierarchical representation learning, making them indispensable in modern deep learning applications. CNN architecture basically consisting following layers.

Convolution Operation: Applying learnable filters (kernels) to input images, extracting features such as edges, textures, or patterns through element-wise multiplication and aggregation.

Activation Function: ReLU (Rectified Linear Unit) is applied after convolution operations to introduce non-linearity and enable complex feature learning.

Pooling Layers:

Pooling Operation: Reduces spatial dimensions (width and height) of feature maps, effectively down sampling them. Common methods include Max Pooling (retaining maximum values) and Average Pooling (calculating average values).

1) *Fully Connected Layers:*

Flattening: Converts resulting 2D feature maps into a 1D vector for input into fully connected layers.

Dense (Fully Connected) Layers: Neurons in theselayers connect to all activations from the previous layer, facilitating learning of global features and making final predictions.

2) *Activation Functions:*

ReLU: Applied in most layers to introduce non-linearity, aiding in learning complex mappings from input to output.

Sigmoid: Often used in the output layer for binary classification, producing probabilities between 0 and 1.

SoftMax: Utilized in the output layer for multi-class classification, providing normalized probabilities across all classes. model's predictions versus the actual labels in the test set. The matrix categorizes predictions into true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), offering a detailed assessment

Transfer Learning: Transfer learning is a technique in deep learning where a model trained on one task is re-purposed or fine-tuned on a new, related task [2]. Here, in transfer learning VGG16 CNN pre trained architecture used for image classification. VGG16 is a convolution neural network architecture that was proposed by the Visual Geometry Group (VGG) at the University of Oxford. The VGG-16 network comprises 16 layers organized as follows: it includes 13 convolution layers, each using 3x3 filters, interspersed with 2x2 max pooling layers and input size is 224x224 image. Relu activation functions are applied after each convolution layer. Additionally, the network features three fully connected layers, which collectively house the majority of the network's parameters. It is known for its simplicity and effectiveness in image classification. VGG16 is typically pre- trained on the ImageNet dataset, which consists of millions of labeled images across thousands of categories. The pre- trained model learns to extract hierarchical features from images.

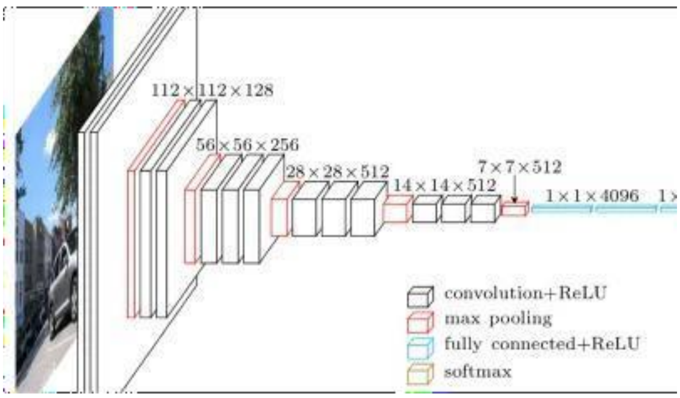


Figure2: Architecture of VGG16

Training: Dividing the dataset into training, validation, and test sets. Train the CNN using the training set, adjusting model parameters (e.g., learning rate, optimizer) to minimize the loss function (e.g., categorical cross-entropy). Validate the model on the validation set to monitor performance and prevent overfitting by adjusting regularization techniques (e.g., dropout).

Evaluation: Evaluate model performance using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. These metrics provide insights into the model's ability to correctly classify normal, benign, and malignant cases. For this used confusion matrix. Confusion matrixes visualize the of the model's performance across different classes. This matrix, several performance metrics can be derived:

Accuracy: The Ratio of correct prediction among the total number of predictions.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision: The proportion of true positive predictions in all positive predictions generated by the model.

$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall (Sensitivity): The proportion of true positive predictions among all actual positive instances.

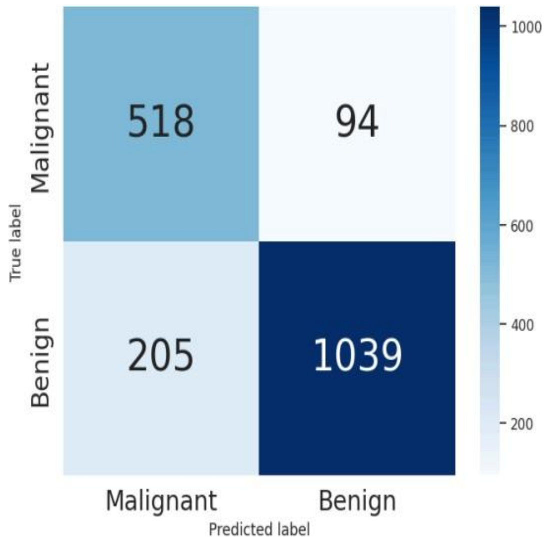
$$\text{Recall} = \frac{TP}{TP+FN}$$

Specificity: the ratio of true negative predictions in all actual negative instance.

$$\text{Specificity}=\frac{True\ negative}{True\ negative+False\ Positive}$$

F1 Score: The harmonic mean of precision and recall (r), providing a single metric that balances both.

$$\text{F1 Score} = \frac{Precision.Recall}{Precision+Recall}.$$



appropriate style is still applied to each and every section, to re-apply styles if necessary.”

III EXPERIMENTAL RESULT

In this research paper, we have developed a CNN VGG16 model with feature extraction on CBSI-DDSM dataset from Kaggle to classify malignant and benign. The best outcome of CNN has been achieved 224x224 with 3 hidden layers. The proposed method has shown 86% accuracy.

	precision	recall	f1-score	support
Benign (Class 0)	0.78	0.82	0.80	609
Malignant (Class 1)	0.91	0.88	0.90	1247
accuracy			0.86	1856
macro avg	0.84	0.85	0.85	1856
weighted avg	0.87	0.86	0.86	1856

CONCLUSION

We developed a deep learning-based model approach for breast cancer detection for mammography images, leveraging the CBIS-DDSM dataset for training and evaluation. Our study focused on utilizing the VGG16 architecture, a well-established convolution neural network model. Experimental results demonstrated promising evolution metrics including accuracy and AUC (Area Under the Curve). The VGG16-based models exhibited robust performance, showcasing their potential to aid radiologists in early breast cancer detection and potentially enhancing diagnostic accuracy. Moving forward, future research directions could explore the utilization of larger datasets, investigate an advanced deep learning architectures beyond VGG16, and consider the development of multi-modal and hybrid model approaches for comprehensive breast cancer detection. Using VGG16 architecture we achieved 86% accuracy for breast cancer detection.

In summary, our research contributes to the evolving field of deep learning in medical image analysis, underscoring the VGG16 model's efficacy in enhancing breast cancer detection methodologies. “This work holds promise for significant advancements in clinical practice and patient outcomes.

REFERENCES

[1] Dabeer, Sumaiya, Maha Mohammed Khan, and Saiful Islam. "Cancer diagnosis in histopathological image: CNN based approach." *Informatics in Medicine Unlocked* 16 (2019): 100231.

[2] S. Gengtian, B. Bing and Z. Guoyou, "EfficientNet-Based Deep Learning Approach for Breast Cancer Detection With Mammography Images," *2023 8th International Conference on Computer and Communication Systems (ICCCS)*, Guangzhou, China, 2023, pp. 972-977,doi: 10.1109/ICCCS57501.2023.10151156.

[3] I. Boglaev, “A numerical method for solving nonlinear integro-differential equations of Fredholm type,” *J. Comput. Math.*, vol. 34, no. 3, pp. 262–284, May 2016, doi: 10.4208/jcm.1512-m2015-0241.

[4] Y. J. Tan, K. S. Sim and F. F. Ting, "Breast cancer detection using convolutional neural networks for mammogram imaging system," *2017 International Conference on Robotics, Automation and Sciences (ICORAS)*, Melaka, Malaysia, 2017, pp. 1-5, doi: 10.1109/ICORAS.2017.8308076.

[5] A. Melek, S. Fakhry and T. Basha, "Spatiotemporal Mammography-based Deep Learning Model for Improved Breast Cancer Risk Prediction," *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Sydney, Australia, 2023, pp. 1-4, doi: 10.1109/EMBC40787.2023.10340602.

[6] M. O. F. Goni, F. M. S. Hasnain, M. A. I. Siddique, O. Jyoti and M. H. Rahaman, "Breast Cancer Detection using Deep Neural Network," *2020 23rd International Conference on Computer and Information Technology (ICCIT)*, DHAKA, Bangladesh, 2020, pp. 1-5, doi: 10.1109/ICCIT51783.2020.9392705.

[7] Priyanka, Kumar Sanjeev. "A review paper on breast cancer detection using deep learning." *IOP conference series: materials science and engineering*. Vol. 1022. No. 1. IOP Publishing, 2021.

[8] Abunasser, Basem S., et al. "Convolution neural network for breast cancer detection and classification using deep learning." *Asian Pacific journal of cancer prevention: APJCP* 24.2 (2023): 531.

[9] Yue, Wenbin, Zidong Wang, Hongwei Chen, Annette Payne, and Xiaohui Liu. "Machine learning with applications in breast cancer diagnosis and prognosis." *Designs* 2, no. 2 (2018): 13.

[10] D. Albashish, R. Al-Sayyed, A. Abdullah, M. H. Ryalat and N. Ahmad Almansour, "Deep CNN Model based on VGG16 for Breast Cancer Classification," *2021 International Conference on Information Technology (ICIT)*, Amman, Jordan, 2021, pp. 805-810, doi: 10.1109/ICIT52682.2021.9491631.

[11] A. Algarni, B. A. Aldahri and H. S. Alghamdi, "Convolutional Neural Networks for Breast Tumor Classification using Structured Features," *2021 International Conference of Women in Data Science at Taif University (WiDSTaif)*, Taif, Saudi Arabia, 2021, pp. 1-5, doi: 10.1109/WiDSTaif52235.2021.9430225.