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Comparison of DenseNet201 and ResNet50 for Breast Cancer Detection using Deep Learning

K. Raja Guru Sai Sree[1], Dr. K. Chaitanya[2*]

[1]Student, Department of Computer Science Engineering, SRK INSTITUTE OF TECHNOLOGY, Vijayawada, Andhra Pradesh, India
[2]Associate Professor, Department of Computer Science Engineering, SRK INSTITUTE OF TECHNOLOGY, Vijayawada, Andhra Pradesh, India

Emails: kancharagunta1998@gmail.com[1], kilaru.chaitanya84@gmail.com[2*]

Abstract

Breast cancer is one of the most prevalent and life- threatening diseases affecting women worldwide. Early detection plays a crucial role in improving survival rates and treatment effectiveness. Recently, deep learning has emerged as a powerful tool in medical imaging, particularly in the classification and detection of breast cancer. In this study, we compare the performance of DenseNet201 and ResNet50 architectures on a breast ultrasound image dataset for classification tasks. The models were trained for 20 epochs, achieving test accuracies of 83.17% and 65.42% for DenseNet201 and ResNet50, respectively. The corresponding training accuracies were 90.07% and 68.10%. Our findings indicate that DenseNet201 out performs ResNet50 in terms of test accuracy, demonstrating a more robust learning capability for this dataset. These results contribute to the ongoing research in deep learning-based breast cancer detection and highlight the importance of selecting an appropriate CNN architecture for medical image classification.

Keywords: Breast cancer, deep learning, DenseNet201, ResNet50, convolutional neural networks, medical imaging.

I. INTRODUCTION

Breast cancer remains one of the most significant health concerns worldwide, accounting for a substantial number of cancer-related deaths among women [1]. The early detection of breast cancer significantly improves survival rates and enables timely medical intervention [2]. Traditional diagnostic techniques such as mammography, ultrasound, and biopsy are widely used for screening and diagnosis. However, these methods can be time-consuming, operator-dependent, and sometimes prone to misdiagnosis [3], [4].

With advancements in artificial intelligence, deep learning has emerged as a powerful tool in medical imaging, providing automated and accurate detection of breast cancer [5]. Convolutional Neural Networks (CNNs) have shown promising results in image classification and feature extraction, making them highly suitable for medical applications [6]. In particular, transfer learning with pre-trained deep learning models such as DenseNet201 and ResNet50 has demonstrated effectiveness in classifying medical images with high accuracy [7], [8].

In this study, we investigate and compare the performance of DenseNet201 and ResNet50 architectures for breast cancer detection using a breast ultrasound image dataset. The objective is to determine the model that achieves higher classification accuracy while maintaining efficiency in training. By evaluating these models, we aim to contribute to the ongoing research in deep learning applications for medical image analysis and assist in developing improved breast cancer detection systems.

II. LITERATURE REVIEW

Deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved medical image classification. This section discusses related works in CNN-based medical imaging and the effectiveness of architectures such as ResNet and DenseNet.

A. *CNNs in Medical Imaging*

CNNs have demonstrated state-of-the-art performance in medical imaging tasks, including disease diagnosis and segmentation [9], [10]. The ability of CNNs to learn hierarchical spatial representations makes them highly effective for feature extraction from medical images. Recent studies have shown that CNNs outperform traditional machine learning methods, such as Support Vector Machines (SVMs) and Random Forest, in detecting breast abnormalities [5].

B. *ResNet and DenseNet for Medical Image Analysis*

ResNet, introduced by Heetal.[11], introduced residual learning to address vanishing gradient problems in deep networks. By incorporating skip connections, ResNet models enable training of very deep architectures while maintaining stable gradients. Studies have demonstrated that ResNet models achieve high classification accuracy in breast cancer detection [12].

DenseNet, proposed by Huang et al. [13], enhances feature reuse through dense connections, where each layer receives inputs from all preceding layers. DenseNet has been widely applied in medical imaging and has shown superior performance in ultrasound image classification tasks compared to standard CNNs [14].

C. *Deep Learning for Ultrasound Image Classification*

Ultrasound imaging is a widely used diagnostic tool for breast cancer detection due to its non-invasive nature. Traditional image processing techniques often fail to generalize across different datasets, motivating the use of CNNs for automatic feature extraction. Several studies have explored CNN-based approaches for ultrasound image classification [15].

Goyal et al. [14] demonstrated that DenseNet-based models outperformed ResNet for breast ultrasound image classification, achieving a higher sensitivity and specificity. This suggests that feature reuse in DenseNet improves classification performance in ultrasound imaging applications.

Despite the success of deep learning models in medical imaging, challenges remain, such as dataset bias, overfitting, and interpretability. Future research should focus on explain- able AI (XAI) techniques to improve model transparency and clinical trustworthiness [16].

III. METHODOLOGY

In this section, we describe the methodology employed for breast cancer detection using deep learning models. The study utilizes a breast ultrasound dataset, preprocessed and analyzed using two deep learning architectures: DenseNet201 and ResNet50.

A. *Dataset and Preprocessing*

The dataset consists of ultrasound images of breast cancer tumors categorized into benign and malignant cases. Preprocessing plays a crucial role in improving model accuracy by enhancing image quality and ensuring consistency in input dimensions. The following steps were performed:

1) **Resizing**: All images were resized to 224×224 pixels to match the input size required for ResNet50 and DenseNet201.

2) **Normalization**: Pixel intensity values were scaled to the range [0, 1] by applying min-max normalization:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

Where X' is the normalized image, X is the original image, and $X_{\min}$, $X_{\max}$ are the minimum and maximum pixel values.

3) **Data Augmentation**: To increase

model generalization and reduce over fitting, various augmentation techniques were applied:

- Rotation: Images were rotated randomly within ±20° .
- Flipping: Horizontal and vertical flips were applied randomly.
- Zooming: A random zoom factor of up to 20% was applied.
- Contrast Adjustment: Image contrast was adjusted within a small range.

4) **Noise Reduction**: Gaussian filtering was applied to reduce noise, using the formula:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

Where σ is the standard deviation of the Gaussian kernel.

5) Splitting: The dataset was divided into training (80%), validation (10%), and testing (10%) sets.

B. *Convolutional Neural Networks (CNNs)*

Convolutional Neural Networks (CNNs) area class of deep learning architectures designed for processing structured grid-like data, particularly images. CNNs have demonstrated remarkable success in medical image classification tasks, including breast ultrasound image analysis [9], [10].

A CNN typically consists of three main types of layers: convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply a set of filters to extract hierarchical features from input images. The convolution operation for an input image X and a filter W is mathematically defined as:

$$Y(i,j) = \sum_{m} \sum_{n} X(i-m, j-n)\, W(m,n) \quad (3)$$

Where $Y(i, j)$ represents the output feature map, and the summation iterates over the spatial dimensions of the filter.

1) ***Activation Function:*** After the convolution operation, an activation function introduces non-linearity to help the network learn complex patterns. A widely used activation function is the Rectified Linear Unit (ReLU), defined as:

$$f(x) = \max(0, x) \quad (4)$$

ReLU helps mitigate the vanishing gradient problem and accelerates training.

2) ***Pooling Layers****:* Pooling layers reduce the spatial dimensions of feature maps, improving computational efficiency while retaining important features. A commonly used operation is max pooling:

$$Y(i, j) = \max_{(m, n)\in R} X(i+m, j+n) \quad (5)$$

where R defines the pooling region, and the operation selects the maximum value in that region.

3) ***Fully Connected Layers and Softmax:*** After feature extraction, fully connected layers are used for classification. The final layer applies the softmax function:

$$P(y = k|X) = \frac{\sum e^{z_k}}{\substack{k \\ j=1} e^{z_j}} \quad (6)$$

Where z_k is the activation for class k, and $K$is the total number of classes. The softmax function ensures that the output is a probability distribution over the classes.

CNNs are widely used in medical image classification due to their ability to learn spatial hierarchies of features [17],[18].

C.ResNet50Architecture

ResNet50 (Residual Network with 50 layers) is a deep CNN designed to address the vanishing gradient problem in very deep networks by using residual learning [11]. The architecture consists of multiple residual blocks, each incorporating skip connections to enable identity mapping and facilitate gradient flow during training.

1) Residual Learning: Traditional deep networks often suffer from vanishing or exploding gradients, making training difficult as depth increases. ResNet50 over comes this by using residual learning, where instead of learning a direct mapping $H(X)$ from input X to output Y, the network learns the residual function:

$$H(X)=F(X,\{W_i\})+X \quad (7)$$

where:

- $H(X)$ is the desired underlying mapping.
- $F(X,\{W_i\})$ represents the residual function.
- X is the input.
- The identity mapping X allows gradient flow, preventing degradation in deep networks.

By reformulating the learning objective to predict residuals rather than the full transformation, ResNet50 improves optimization efficiency [19].

2) ***Skip Connections:*** A critical feature of ResNet50 is the use of skip (shortcut) connections, which allow information to bypass multiple layers. Mathematically, a residual block is defined as:

$$Y=\sigma(F(X,W)+X) \quad (8)$$

Where σ is the activation function (typically ReLU):

$$\sigma(x)=\max(0,x) \quad (9)$$

The key advantages of skip connections include:

- Mitigation of vanishing gradient issues.
- Improved feature propagation and reuse.
- Faster convergence during training.

Enabling the training of much deeper networks without degradation.

3) *Structure of ResNet50:* ResNet50 follows a structured pipeline that includes:

- Initial convolution layer followed by max pooling.
- Four residual blocks, each containing convolutional layers with kernel sizes (3 ×3) and (1 ×1).
- Batch normalization for stable learning [5].
- Global average pooling followed by a fully connected layer for classification.

4) ***Mathematical Formulation of ResNet Blocks:*** Each residual block contains convolutional layers followed by batch normalization and activation. The identity shortcut can be either direct (if dimensions match) or achieved using a 1×1 convolution:

$$Y=\sigma(W_2*\sigma(W_1*X+b_1)+b_2)+X \quad (10)$$

where:

- W_1, W_2 are the weights of convolutional layers.
- b_1, b_2 are biases.
- $*$represents convolution operation.

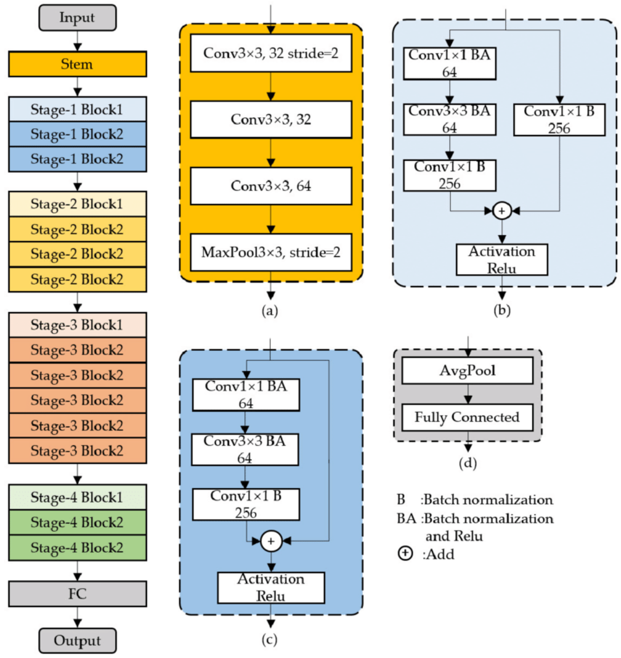


Fig.1.ResNet50 Architecture with Residual Connections

D. *DenseNet201Architecture*

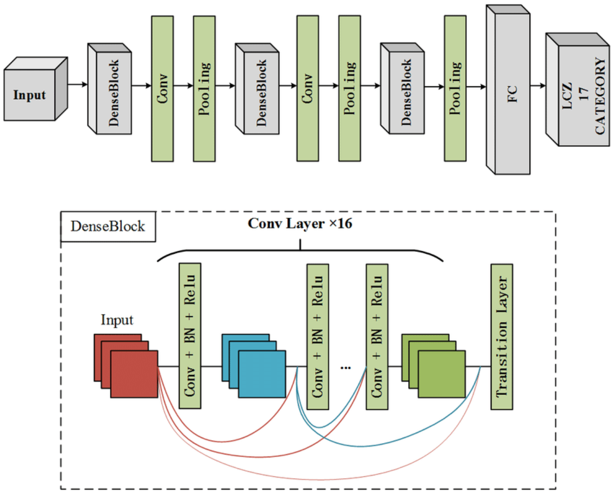
DenseNet201 (Densely Connected Convolutional Network) is a deep CNN architecture designed to improve feature propagation, encourage feature reuse, and reduce the number of parameters through dense connectivity. Unlike traditional architectures where each layer learns features independently, DenseNet connects each layer to every other layer in a feed- forward manner [19].

1) ***Dense Connectivity:*** In DenseNet, each layer receives the feature maps from all preceding layers as input. This enhances feature reuse and alleviates the vanishing gradient problem. The dense connectivity is mathematically represented as:

$$X_l=H_l([X_0,X_1,\dots,X_{l-1}]) \quad (11)$$

where:

- X_l is the output of the l-th layer.
- $H_l(\cdot)$ represents a non-linear transformation consisting of Batch Normalization (BN), ReLU activation, and Convo- lution.



- $[X_0, X_1, \ldots, X_{l-1}]$ denotes the concatenation of feature maps from all preceding layers [20].

Unlike residual connections in ResNet, which use element- wise addition, DenseNet employs feature map concatenation, allowing the network to preserve information across all layers.

2) ***Growth Rate:*** DenseNet introduces a parameter called the growth rate (k), which controls the number of new feature maps learned at each layer. If a layer receives m input feature maps, its output consists of $m + k$ feature maps:

$$m_l = m_0 + k \cdot (l - 1) \quad (12)$$

where:

- m_l is the number of feature maps at layer l.
- m_0 is the number of input feature maps.
- K is the growth rate [21].

This design ensures efficient parameter usage while main- taining a strong gradient flow through the network.

3) ***Dense Blocks and Transition Layers:*** DenseNet is structured into multiple Dense Blocks, each containing several convolutional layers. Between these blocks, Transition Layers are introduced, consisting of batch normalization, 1×1 convolutions, and 2×2 average pooling. The transition layer is mathematically represented as:

$$T(X) = BN(Conv_{1\times1}(AvgPool_{2\times2}(X))) \quad (13)$$

where:

- BN is batch normalization.
- $Conv_{1\times1}$ isa1×1convolutionlayer.
- $AvgPool_{2\times2}$ isa2×2 average pooling operation [22].

4) ***AdvantagesofDenseNet201:***

- Improved gradient flow due to shorter paths from input to output layers.
- Feature reuse, leading to a reduction in the number of parameters compared to traditional deep networks.
- Better generalization in medical image classification tasks, including breast cancer detection [23].

Fig.2. DenseNet201 Architecture with Dense Blocks and Transition Layers

IV. RESULTS AND ANALYSIS

A. *Training Accuracy and Loss*

Figure 3 and Figure 4 show the training accuracy trends for ResNet50 and DenseNet201 models, respectively. The ResNet50 model achieved a final training accuracy of 68.10%, while the DenseNet201 model reached 90.07%.

Model	Final Training Accuracy	Final Training Loss
ResNet50	90.07%	0.8430
DenseNet201	68.10%	0.4748

TABLE I PERFORMANCE SUMMARY OF RESNET50 AND DESNET201 MODELS

Both models demonstrated effective learning. However, DenseNet201 out performed ResNet50 in terms of final training accuracy.

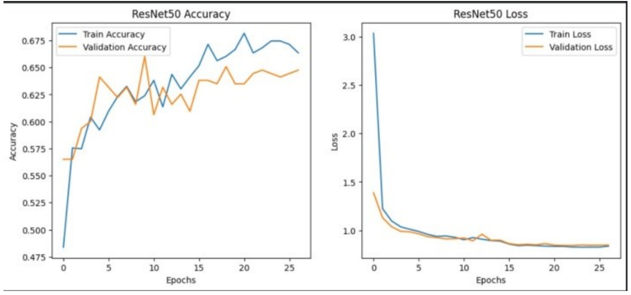


Fig.3.Training Accuracy and Loss for ResNet50 Model

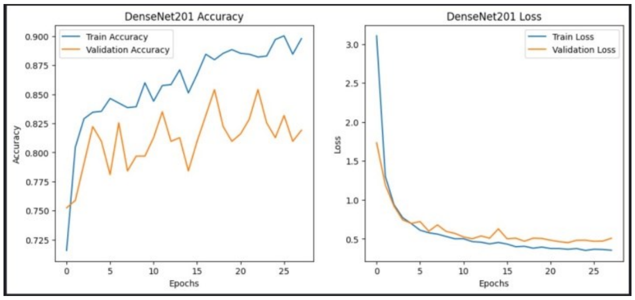


Fig.4.Training Accuracy and Loss for DenseNet201 Model

B. *Performance Comparison*

Table I summarizes the training accuracy and loss values for both models.

DenseNet201 achieved a higher accuracy and lower loss compared to ResNet50. The confusion matrices indicate that DenseNet201 had fewer classification errors.

REFERENCES

[1] R. L. Siegel, K. D. Miller, and A. Jemal, “Cancer statistics, 2023,” *CA: A Cancer Journal for Clinicians*, vol. 73, no. 1, pp. 17–48, 2023.

[2] W. Wang and X. Liu, “Early detection of breast cancer: Advances and future perspectives,” *Nature Reviews Clinical Oncology*, vol. 19, pp.211–225, 2022.

[3] C. H. Lee, E. F. Dershaw, and M. Kopans, “Mammography screening: Controversies and clinical evidence,” *The Lancet Oncology*, vol. 21, pp. e305–e316, 2020.

[4] Tenali, N., Babu, G.R.M. A Systematic Literature Review and Future Perspectives for Handling Big Data Analytics in COVID-19 Diagnosis. New Generating Computing, 243–280 (2023). https://doi.org/10.1007/ s00354-023-00211-8

[5] P. C. Gøtzsche and M. Nielsen, “Screening for breast cancer with mammography,” *Cochrane Database of Systematic Reviews*, vol. 6,2013.

[6] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. Setio, F. Ciompi, M. Ghafoo-rian, J.A. vander Laak, B. van Ginneken, and C.I. Sa´nchez, “A survey on deep learning in medical image analysis,” *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.

[7] D. Shen, G. Wu, and H. Suk, “Deep learning in medical image analysis,” *Annual Review of Biomedical Engineering*, vol.19, pp.221-248,2017.

[8] A. Esteva, K. Chou, S. Yeung, N. Naik, A. Madani, T. Mottaghi, B. Liu, G. Topol, and J Dean, “Deep learning-enabled medical computer vision,” *Nature Medicine*, vol. 27, pp. 1316–1323, 2021.

[9] M. Raghu, C. Zhang, J. Kleinberg, and S. Bengio, “Transfusion: Un-derstanding transfer learning for medical imaging,” *Advances in Neural Information Processing Systems (NeurIPS)*, 2019.

[10] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,”*Proceedings of the IEEE*, vol. 86,no. 11, pp. 2278–2324, 1998.

[11] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in *Advances in neural infor-mation processing systems*, 2012, pp. 1097–1105.

[12] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.

[13] P. Raghu, H. B. Weiss, N.-C. N. Shih, I. Y. Kim, C. Cordon-Cardo,M. Ladanyi, T. J. Fuchs, M. G. Hanna, M. R. Hameed, Y. Wen*et al.*, “Direct prediction of molecular biomarkers from breast cancer histopathology images using deep learning,” *Scientific reports*, vol. 9, no. 1, pp. 1–12, 2019.

[14] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700–4708, 2017.

[15] P. Goyal, V. Sharma, A. Gupta, and P. Verma, “Ultrasound image classification using deep learning: A comparative study of resnet and densenet architectures,” *Biomedical Signal Processing and Control*, vol. 75, p. 103259, 2022.

[16] D. Shen, G. Wu, and H.-I. Suk, “Deep learning in medical image analysis,” *Annual review of biomedical engineering*, vol. 21, pp. 221–248, 2019.

[17] Tenali, N., Babu, G.R.M. HQDCNet: Hybrid Quantum Dilated Convolution Neural Network for detecting covid-19 in the context of Big Data Analytics. Multimed Tools Appl 83, 2145–2171 (2024). https://doi.org/10.1007/s11042-023-

15515-6

[18] A Holzinger, C. Biemann, C.S. Pattichis, and D.B. Kell, “What dowe need to build explainable ai systems for the medical domain?” *ar Xiv preprint arXiv:1712.09923*, 2017.

[19] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” *arXiv preprint arXiv:1409.1556*, 2014.

[20] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, Vanhoucke, and A. Rabinovich, “Going deeper with convolutions,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 1–9.

[21] N. Tenali, V. S. Desu, C. Boppa, V. Chowdary Chintala and B. Guntupalli, "Oral Cancer Detection using Deep Learning Techniques," 2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA), Uttarakhand, India, 2023, pp. 168-175, doi: 10.1109/ICIDCA56705.2023. 10100045.

[22] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 4700–4708,2017.

[23] X. Wang and Y. Guo, “A review on densenet and its applications in medical imaging,” *IEEE Access*, vol. 8, pp. 56045–56055, 2020.

[24] Z. Zhang and Y. Liu, “Densenet for medical image classification: A review,” *Journal of Machine Learning Research*, vol. 19, no. 2, pp. 1–20, 2018.

[25] J. Deng and K. Zhang, “Transition layers in densenet: Impact on model performance,” *Pattern Recognition Letters*, vol. 128, pp. 1–9, 2019.

[26] H. Gao and L. Wang, “Densenet-based deep learning for breast cancer detection in ultrasound images,” *IEEE Transactions on Biomedical Engineering*, vol. 68, pp. 730–740, 2021.