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Comparison of Transfer Learning Model Performance for Breast Cancer Type Classification in Mammogram Images

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Abstract

Globally, breast cancer is the type of cancer that most women suffer from. Early detection of breast cancer is very important because there is a big chance of cure. Mammography screening makes it possible to detect breast cancer early. The study of computer-assisted breast cancer diagnosis is gaining increasing attention. Breast cancer comes in two forms: benign cancer and malignant cancer. advances in deep learning (DL) technology and its use to overcome obstacles in medical imaging, and classification using a number of transfer learning models to identify the type of breast cancer (malignant, benign, or normal). This work conducted a thorough comparison analysis of eight prevalent pre-trained CNN algorithms (VGG16, ResNet50, AlexNet, MobileNetV2, ShuffleNet, EfficientNet-b0, EfficientNet-b1, and EfficientNet-b2) for breast cancer classification. In this study, we permonData is divided into training, testing, and validation. Using the publicly accessible mini-DDSM dataset, we assess the proposed architecture. were used to measure the classification accuracy (Acc). For genBased on test results, the best accuracy was obtained using EfficientNetb2 with an accuracy value of 94% for training data and 98% for test data on mammogram images.

Keywords: *Breast Cancer Classification; Deep Learning; Mammography Image; Transfer Learning*

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1. Introduction

Breast cancer initiates with unregulated cellular alterations and proliferation in the breast, resulting in a mass (lesion) that may either proliferate and metastasize to other body regions (as seen in malignant lesions) or grow without dissemination (as shown in benign lesions). Breast cancer is most effectively treated while the lesion is tiny; however, symptoms are absent at that stage. Consequently, screening is crucial for early identification [1]. The World Health Organization reports that Breast Cancer impacts 2.1 million people annually and is the leading cause of cancer fatalities among women. Breast cancer not only ranks #1 among malignancies in Indonesia but is also a leading cause of mortality [2]. Globocan data from 2020 indicates that Indonesia recorded 68,858 new breast cancer cases, constituting 16.6% of the overall 396,914 new cancer cases. Nevertheless, the total number of cases exceeded 22,000 fatalities [3]. These statistics show that the spread of Breast Cancer is indeed one of the main health challenges in the world—around 43%. Death from cancer can be defeated if patients routinely carry out early detection and avoid risk factors that cause cancer.

Early detection of breast cancer can decrease mortality rates and lower treatment expenses, while also eliminating the necessity for biopsies in patients. Moreover, numerous studies indicate that radiologists may misdiagnose breast cancer due to the high volume of ultrasound images generated daily and the insufficient number of radiologists available to interpret these medical images. The substantial volume of ultrasound images generated is attributable to the rising incidence of breast cancer diagnoses, potentially overwhelming radiologists [4].

Imaging models have been crucial in all stages of breast cancer management, encompassing screening, early detection, diagnosis, and subsequent treatment. Moreover, given that cancer is a multifaceted illness with various pathologies, advancements in current approaches and the introduction of novel imaging

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models are perpetually being developed to enhance detection efficacy and, therefore, breast cancer outcomes and survival rates [1]. Each of these modalities possesses distinct therapeutic advantages and downsides. The selection of modality and technique is also affected by the patient's stage, age, and breast tissue density. The primary clinical breast imaging modalities employed for the detection and diagnosis of breast cancer include mammography, ultrasound, magnetic resonance imaging (MRI), positron emission tomography (PET), and computed tomography [5], [6]. According to Tirona et al.'s study, mammography is often used because it is very efficient in detecting tumors early [7]. However, breast cancer screening using mammography images is considered less effective and accurate due to its inability to detect small cancer cells and dense breast tissue in patients [8].

Classification is very important to consider to identify and differentiate cancer types in mammography images. This stage aims to categorize images according to certain categories. Feature vectors or image pixels are used to indicate the mapping of features from images to class labels in image classification tasks. In computer vision and its applications, image classification is very important; this includes categorizing motion and information retrieval systems [9]. Convolutional neural network-based methods have shown good performance in image classification, which aims to find out the features of training images and the effect of feature selection in increasing accuracy and reducing computational time.

There are several studies related to breast cancer classification methods using the Deep Learning method, including using the CNN Transfer learning GoogleNet and Alexnet methods and the use of preprocessing and augmentation resulting in an accuracy of 71% without Augmentation and 90% with Augmentation [10]. Using Transfer learning Xception, InceptionV3, InceptionResnet, VGG 16, VGG19 and Global Polling produced accuracies of 92.50%, 90%,89%,85% and 82% [11]. Transfer learning Resnet, Resnet VGG, VGG-VGG, and VGG Resnet were also used by proven to be able to improve classification accuracy [12]. Using InceptionV3, DenseNet121, ResNet50, VGG16 and Mobile- NetV2 models with augmentation, InceptionV3 model produced accuracies of 98.87% [13]. Using preprocessing, Ensemble Swin Transformers and ConvNet and Soft voting produced accuracies of 85.40% and 94.17% [14].

From the discussions above, this study aims to develop an accurate breast cancer type classification technique using several Transfer Learning models based on three classes: benign, malignant, and normal.

2. Research Methods

2.1 Research Stages

In this study, several stages were used as seen in Figure 1, consisting of the literature review stage which includes evaluation of studies in the last 1 to 5 years. Continued with the proposal preparation phase and research roadmap, the process of collecting breast cancer datasets, the stage of developing a breast cancer classification system using several Transfer Learning methods and the next step is testing the method, and the final step is analyzing the results and drawing conclusions based on the findings obtained.

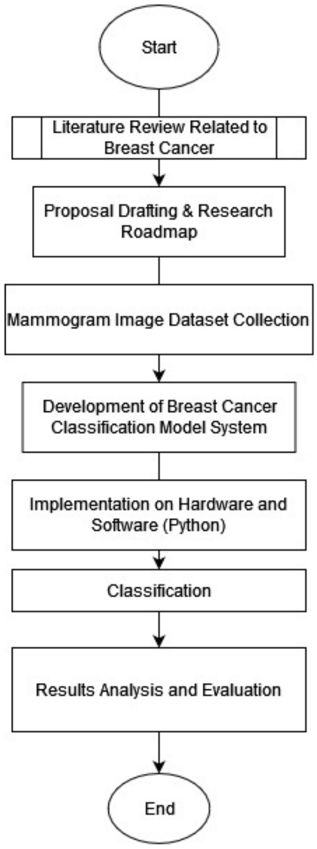

Figure 1. Research Stages

2.2 Dataset

To demonstrate the effectiveness of the proposed method, all experiments were conducted using two publicly available standard databases namely mini-DDSM (Digital Screening Mammography Database) (Lekamlage & Westerberg, n.d.) for mammograms available at https://www.kaggle.com/datasets/cheddad/miniddsm. A total of 2620 breast cases had 9684 mammogram images in the mini-DDSM dataset with CC and MLO views of the right and left breasts in 16-bit .png format. In this study, subsets consisting of normal, benign, and malignant classes were randomly sampled from the mini-DDSM dataset to test the performance of the proposed model with a small dataset. Normal, benign, and malignant breast images from the mini-DDSM dataset are presented in Figure 2. The dataset division for each category based on training, validation, and testing data is shown in Table 1.

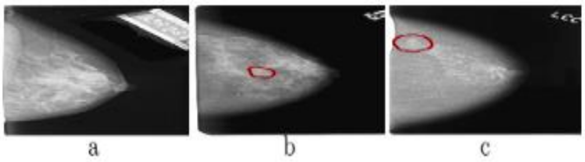

Figure 2. Mammogram images from the mini-DDSM dataset
(a) Normal, (b) Benign, (c) Malignant

Table 1. Dataset distribution

Category	Training	Validation	Testing	Total
Benign	600	200	200	1000
Malignant	600	200	200	1000
Normal	600	200	200	1000
Total	1800	600	600	3000

Data distribution in the study for the category (Benign, Malignant, Normal) is 600 samples for Training, 200 samples for Validation, and 200 samples for Testing. so that the total number of samples per category is 1000 and the total data is 3000 samples.

2.3 System Development

The method proposed in this study consists of several processes, including input data processing, data pre-processing process, CNN architecture creation process, hyperparameter setting process and evaluation matrix as shown in Figure 3.

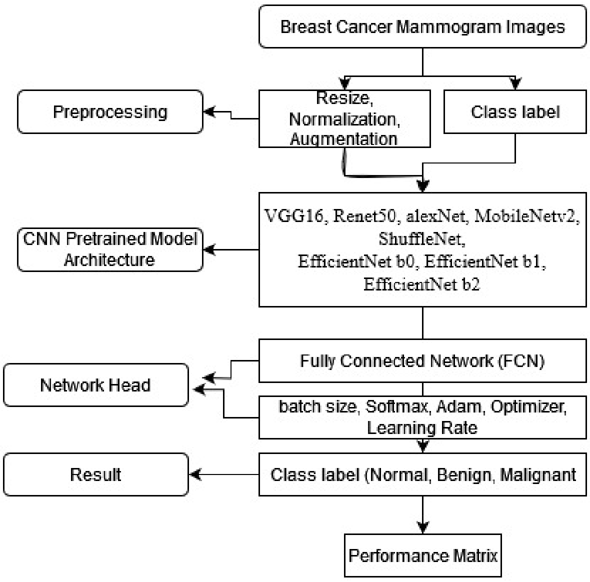

Figure 3. Development of a breast cancer classification system

The data pre-processing stage is an important step in preparing data for the analysis process. The steps in data pre-processing in this study are normalization, resizing, data augmentation, and data digitization.

The resizing process on breast cancer images in the Breast Ultrasound Images Dataset (BUSI) is carried out to create consistency in image size and meet the technical requirements of the analysis to be performed. This dataset consists of images from various sources, with resolution sizes that may vary. One example in Figure 3, is a normal breast cancer image before being resized, the image had a resolution of 208x351 pixels after being resized to a size of 224x224 pixels.

Data augmentation is a technique used to increase the amount of data without losing the essence of the data. This can be done by performing random transformations on the data by introducing additional variations to the original image such as *rescaling, shearing, zooming, and horizontal flip*, which can improve model performance, especially on small datasets. This augmentation helps the model learn more robust features, thereby improving the model's generalization ability on previously unseen data.

2.4 Breast Cancer Classification Process with Convolutional Neural Network (CNN)

The process of breast cancer classification using CNN classifier with transfer learning technique In the research data analysis process of breast cancer type classification using several CNN architectures including VGG16, GoogleNet, EfficientNet, ResNet50, AlexNet, and SuffleNet.

VGG16 [15] is a convolutional neural network (CNN) model known for its architecture with 16 weighted layers, making it a powerful tool for image recognition. This model is considered one of the best vision model architectures due to its simplicity and effectiveness. VGG16 uses convolutional layers with 3x3 filters and stride 1, along with max-pooling layers with 2x2 filters, maintaining this pattern consistently throughout its structure.

GoogleNet [16] is a deep learning architecture appropriate for accurate and productive medical image analysis, especially when used for BC diagnosis. MobileNet's focus on computational efficiency makes it possible to extract information from mammography images in an efficient manner, facilitating the identification of minute patterns or anomalies linked to breast cancer. MobileNet optimizes computational cost and memory consumption by using depthwise separable convolutions, which makes it perfect for contexts with limited resources. ReLU6 activation features are integrated, which improves efficiency and works with medical imaging instruments. All things considered, MobileNet is a useful option for BC analysis, producing precise findings while using little processing power.

EfficientNet [17] is a group of deep CNN architectures that were first shown in 2019 and have produced cutting-edge results in a range of computer vision tasks. EfficientNet achieves excellent accuracy while retaining computing efficiency by simultaneously optimizing the network's depth, width, and resolution through the use of joint scaling technique. A head network completes the final classification in EfficientNet, while a backbone network gathers features from input images. To capture spatial and channel correlations in the input, the backbone network combines squeeze and excitation (SE) blocks with mobile inverted convolutional inhibitory layers. To complete the final classification, the head network combines fully linked layers with global average pooling.

ResNet50 [18] is a deep CNN design that circumvents the vanishing gradient problem by learning from very deep architectures through the use of residual connections. Convolutional layers, batch normalization layers, ReLU activation functions, and fully linked layers are among its fifty layers. ResNet50 additionally employs a skip connection, which allows it to efficiently learn both high-level and low-level characteristics by skipping some network levels.

AlexNet [19] is a deep CNN architecture that made significant progress in computer vision tasks like image categorization when it was launched in 2012. There are three fully linked layers and five convolutional layers totaling eight layers in this structure. In order to collect low-level features, the first convolutional layer takes advantage of a wide receptive field, which is revolutionary for computer vision tasks like picture categorization. There are three fully linked layers and five convolutional layers totaling eight layers in this structure. In order to collect low-level features, the first convolutional layer takes advantage of a wide receptive field, which is revolutionary for computer vision tasks like picture categorization. There are three fully linked layers and five convolutional layers totaling eight layers in this structure. Subsequent layers employ smaller receptive fields to catch increasingly sophisticated and abstract elements, while the initial convolutional layer uses a large receptive field to record low-level features like edges and textures. The rectified linear unit (ReLU) activation function, which has subsequently become the industry standard in deep learning, was initially employed by AlexNet. Moreover, dropout regularization is used to stop overfitting when training. The triumph of AlexNet on the ImageNet dataset, comprising more than a million photos, showcases the capability of deep neural networks in image identification assignments and opens the vision domain.

SuffleNet [20] is a convolutional neural network specifically made for mobile devices with constrained processing capacity. It focuses on using cutting-edge processes like pointwise group convolution and channel shuffling to reduce computing costs while preserving accuracy.

2.4 Training Settings

The computing platform employed in this investigation comprised an Intel Core i9-12900k processor operating at 3.20 GHz, an NVIDIA RTX3060 graphics card including 12 GB of video RAM (Nvidia Corp., San Jose, CA, USA), and Compute Unified Device Architecture (CUDA) version 11.7 (Nvidia Corp., San Jose, CA, USA). This configuration offers an enhanced computing environment with NVIDIA processor units. All programs pertinent to this investigation were executed utilizing the PyTorch framework version 3.11.4 (PyTorch, San Francisco, CA, USA).

Table 2. Hyperparameter settings

Hyperparameter	Values
Batch Size	32.64
Number of Epoch	25
Initial Learning Rate	0.001
Optimizer	Adam
Metrics	Categorical Crossentropy

Table 2 shows that this study uses Hyperparameter to set the machine learning model, where the model is trained with a batch size of 32 or 64, for 25 epochs, using Adam as an optimizer with a learning rate of 0.001. The loss function used is Categorical Crossentropy, which is suitable for multi-class classification problems.

2.5 Evaluation

The measurement results are represented in a classification table to facilitate reading. Accuracy is the percentage of the correct system classification. The calculation is in Equation 1.

$$Accuracy = (TP+TN) / (TP+FP+TN+FN) \quad (1)$$

TP is the true positive, TN is the true negative, FN is the false negative, and TN is the true negative.

A classification table including data on the outcomes of the system computation as a whole is called a confusion matrix. Three metrics are used to evaluate data measurements: recall, accuracy, and precision. To make reading easier, the measurement data are displayed in a classification table. The percentage of the system that is correctly classified is called accuracy.

Table 3. Confusion Matrix

		Predicted	
		Negative	Positive
Actual	Negative	TN	TP
	Positive	FN	FP

Table 3 explains that true positive (TP), true negative (TN) indicate that the pixels are correctly identified (the label and prediction are the same for the corresponding class), false positive (FP) and false negative (FN) indicate a mismatch between the prediction results and the label.

3. Results and Discussions

This paper investigates brain tumor detection using diverse scenarios and methodologies. Eight pre-trained models (VGG16, ResNet50, AlexNet, MobileNetV2, ShuffleNet, EfficientNet-b0, EfficientNet-b1, and EfficientNet-b2) are used to classify original breast cancer data. The performance of each approach is extensively evaluated to gain insights into their effectiveness and limitations in various breast cancer classification scenarios.

This study employed eight traditional pre-trained models for the same objective, utilizing the transfer learning approach, which has been previously implemented in numerous scientific investigations for diverse objectives. Consequently, eight models were employed to attain the objective of the study. This project aims to analyze scanner pictures to facilitate the early diagnosis of breast cancer. Two data sets were utilized for the individual training and testing of six Transfer Learning models. The authors contend that any model demonstrating maximum efficacy signifies the accomplishment of this research endeavour, given that all models have practical implications. All Transfer Learning models in this research project are built and executed for a singular objective. The outcomes of training and testing conducted with mammography and ultrasound pictures can be assessed independently for each dataset.

Table 4 shows the accuracy of classifiers using Pre-Trained CNN models in batch size 32. EfficientNet b2 achieves the best results with 94% accuracy on training data and 98% accuracy on testing data, indicating its robustness and superior learning ability for this dataset. EfficientNet b1 also performs exceptionally well, matching EfficientNet b2's 98% testing accuracy but slightly lower training accuracy at 92%. EfficientNet b0 performs slightly below the other variants, with 92% training accuracy and 91% testing accuracy. MobileNetv2 and ShuffleNet show decent performance, achieving testing accuracy of 81% and 82%, respectively. Their training accuracy is slightly lower, which may indicate potential underfitting. AlexNet, ResNet50, and VGG16 demonstrate relatively lower performance. VGG16 has the lowest training accuracy (68%) and testing accuracy (78%), indicating its limitations for this dataset.

Table 4. Results of model evaluation on training and testing data using batch size 32

Model	Batch Size 32	
	Training (%)	Testing (%)
VGG16	68.00	78.00
Renet50	85.00	71.00
alexNet	72.00	77.00
MobileNetv2	79.00	81.00
ShuffleNet	73.00	82.00
EfficientNet b0	92.00	91.00
EfficientNet b1	92.00	98.00
EfficientNet b2	94.00	98.00

Table 5 shows the accuracy of classifier uisng pre-Traned CNN models in batch size 64. EfficientNet b2 achieves the best performance with 94% training accuracy and 98% testing accuracy, confirming its reliability across different batch sizes. EfficientNet b1 maintains consistent testing accuracy (98%) but shows no improvement in training accuracy (92%). EfficientNet b0 sees a slight improvement in testing accuracy (94%) compared to batch size 32, demonstrating minor sensitivity to batch size. ResNet50 improves significantly with batch size 64, achieving 88% training accuracy and 89% testing accuracy, showing better generalization than with batch size 32. AlexNet sees a slight improvement in testing accuracy (82%) compared to batch size 32, but its overall performance remains modest. MobileNetv2's performance drops significantly with batch size 64, especially in training accuracy (45%) and testing accuracy (63%), indicating sensitivity to batch size and possible training instability. VGG16 and ShuffleNet maintain similar performance, showing no significant gains or losses.

Table 5. Model evaluation results on training and testing data using batch size 64

Model	Batch Size 64	
	Training (%)	Testing (%)
VGG16	67.00	77.00
Renet50	88.00	89.00
alexNet	72.00	82.00
MobileNetv2	45.00	63.00
ShuffleNet	71.00	75.00
EfficientNet b0	92.00	94.00
EfficientNet b1	92.00	98.00
EfficientNet b2	94.00	98.00

Figure 4 shows that the confusion matrix for mammography images using EfficientNet-b0 and Batch size 32, the model accuracy is very high, especially in the prediction for benign and normal classes. All normal data are predicted correctly (106/106), and the prediction for the benign class only experiences one error (348 correct from 349 benign data). Malignant is also predicted very well, with 168 correct predictions from all data labeled malignant. There is only 1 prediction error seen, namely when data labeled benign is predicted as malignant.

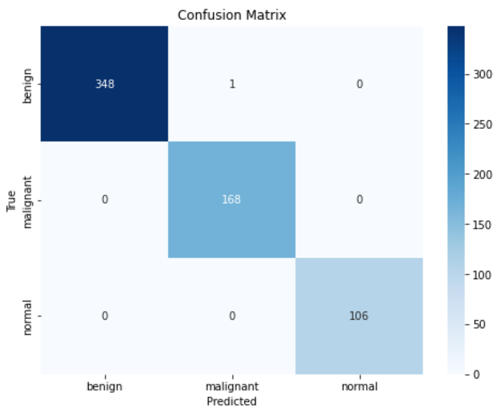

Figure 4. Confusion Matrix data testing using batch size 32

Figure 5 shows that high accuracy using EfficientNet-b0 and batch size 64 is seen in the predictions for benign (342 correct out of total benign predictions) and normal (99 correct out of total normal predictions). There are some prediction errors in the malignant class, where the model more often incorrectly predicts malignant as benign (21).

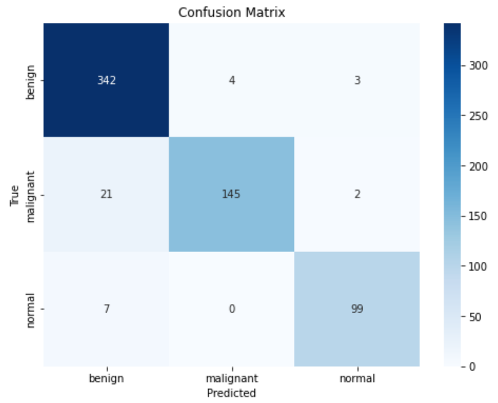

Figure 5. Confusion Matrix data testing using batch size 64

4. Conclusions

This article introduces a unique system designed to diagnose breast cancer through the analysis of mammograms. We initially collected baseline results utilizing transfer learning on advanced CNN architectures. We suggested various pre-trained CNN was trained on mammograms to identify them as cancer, benign, or normal. The EfficientNet variations (b0, b1, b2) exhibited superior performance compared to other models, attaining maximum accuracy in both training and testing stages. EfficientNet b2 exhibited superior performance, achieving 94% accuracy on training data and 98% on testing data, regardless of batch size. EfficientNet b2 emerges as the best-performing model in both batch size configurations, achieving consistent and superior accuracy. While batch size influences performance for some models, EfficientNet models are largely robust to these changes, making them reliable for medical image analysis tasks. Further investigation into optimizing underperforming models, like MobileNetv2 and VGG16, could be explored to enhance their utility in similar scenarios. Future research aimed at addressing misclassifications, especially in malignant instances, is essential for enhancing diagnostic accuracy. Evaluating these models on a more extensive dataset, incorporating photos from various sources, will confirm their generalizability and robustness.

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