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Optimizing CNN Algorithm for Breast Cancer Disease Prediction using ResNet50 with Fine-Tuning Method

Maylinna Rahayu Ningsih[1*], Alamsyah[2]
[1,2]Computer Science Department, Faculty of Mathematics and Natural Sciences,
Universitas Negeri Semarang, Indonesia

Abstract
Breast cancer is one of the deadliest diseases affecting millions of women worldwide. So, early diagnosis and detection is very important to reduce cancer. Thus, early detection and diagnosis efforts are a priority in reducing breast cancer rates. This background becomes a reference in research with The aim is to optimize and improve performance in predicting breast cancer using CNN Algorithm with ResNet50 architecture and Fine-Tuning Method. The method in this research starts from the selection of datasets based on previous research. The dataset is prepared by performing Pre Processing as data cleaning against file names and strings that contain unnecessary characters and interfere with the analysis. The CNN model is supported by the ResNet50 architecture which begins with several layer models, namely the flatten layer, BacthNormalization layer, Dense layer and dropout layer. To improve the accuracy value, Fine Tuning and early stopping models are applied to prevent overfitting. Finally, the prediction is tested by evaluating the model. The test results show an improvement in accuracy compared to previous studies. The performance achieved by the model after Fine Tuning is 96.58% accuracy. The novelty of this article is the use of CNN ResNet50 algorithm and Fine Tuning the model which results in improved accuracy performance in predicting breast cancer disease.

Keywords:
Breast Cancer;
CNN ResNet50;
Fine-Tuning ;

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Corresponding Author:
Maylinna Rahayu Ningsih
Computer Science Department, Universitas Negeri Semarang, Indonesia
Email:
maylinnarahayuningsih@students.unnes.ac.id

INTRODUCTION

Breast cancer is one of the deadliest diseases [1] that affects millions of women around the world. In 2020, the World Health Organization (WHO) obtained data of 7.8 million women diagnosed with cancer and 685 thousand cases of death globally [2]. Approximately 80% of invasive ductal carcinomas that invade breast tissue and milk ducts [3] have in patients who have contracted breast cancer. Since the mid-2000s cancer has increased steadily by about 0.5% each year [4]. Breast cancer itself is more common in women and middle-aged women [5]. There are various types of breast cancer, the cancer will soon be comprehensive [6], [7] to the body if not realized early enough. For this reason, early diagnosis and detection is very important to reduce cancer. Because it can provide significant improvements in the long term. Early diagnosis in recognizing cancer symptoms and screening as identification are 2 different related strategies set out by the WHO regarding early cancer detection [8]. Thus, early detection and diagnosis efforts are a priority in reducing breast cancer rates. Since the issues causing breast cancer are complex, the most effective step in reducing the danger of cancer is early detection and treatment [9]. There are various methods for breast cancer screening such as, computed tomography (CT), ultrasound, mammogram, magnetic resonance imaging (MRI), and thermogram [10]. Looking at the fast, low-cost aspect, ultrasound is considered a common method for breast imaging because it is faster and increases accuracy and sensitivity [11]. Currently, many studies apply machine learning methods with CAD systems. Computer-Aided Diagnosis developed with ultrasound image-based system [12].

In the process, there are studies that focus on classifying the type of breast cancer and those that focus on detecting breast cancer in images. Research [13] using a comparison of the Random forest model with feature selection, then compared with other algorithms whose results Random Forest gets 99.30% accuracy. Other research [14] describes classification methods such as Naïve Bayes and Random Forest as producing effective predictions for diseases. Overview of CAD systems on ultrasound images in research [15] developed segmentation, feature extraction and selection stages in breast cancer detection and classification. In the research [16] using a new method that integrates image segmentation into the CNN algorithm. Other methods such as MLP and CNN are used in this research [17]. While in other literature such as [18] combined a CNN convolutional network with capsule to perform breast cancer histology image classification which resulted in 87% accuracy. The use of other network architectures is discussed in [19] which discusses how DenseNet fixes the problem of gradient descent and computational efficiency that can occur in deep networks such as artificial neural networks or CNNs. Convolution layers in CNNs can also be used as in [20] which resulted in an accuracy of 88.23%. Research [21] using BCDNet as the main algorithm gives an accuracy of 93.97% greater than other methods such as CNN-GTD, ResNet-18+SVM, SD-CNN, SeResNet18 which are used as comparisons. On detection using a combination with CNN Deep [1] shows that the model of choice provides the best accuracy, sensitivity in deep feature models. Research using ResNet50 [22] Its use is intended only for feature extraction with an accuracy of 94.7%. The use of CNN is known to be the most famous algorithm in Deep Learning [23], [24], [25].

Unfortunately, previous research [18] - [22] has not been optimal in the use of CNN architecture. In this study, the method used uses the ResNet50 architecture which is added with several layers such as the Flatten layer to flatten the output of ResNet50, as well as additional layers such as Batch Normalization, Dense, and dropout layers to build a CNN model, then combined with a fine-tuning method to improve the predictive ability of the model by re-optimizing the weight of the model that has been trained on a new dataset. To avoid overfiting, early stopping is used in the process. So that this method can help improve the model's ability to predict and produce better accuracy.

METHOD

The process of applying the proposed method is shown in Figure 1, each step in Figure 1 will be explained in detail in the next discussion.

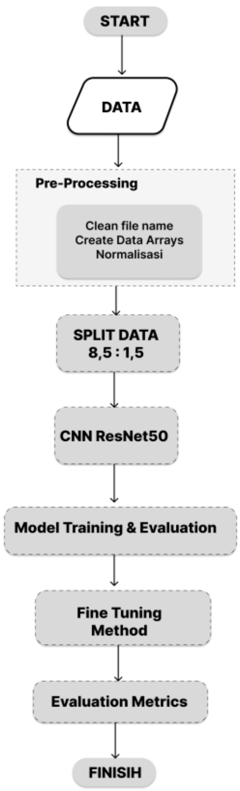

Figure 1. Flowchart of the proposed method

Dataset

The dataset used is taken from kaggle as the same reference from the journal [21] Breast Ultrasound Images Dataset | Kaggle. The dataset totals 1578 images, which are divided into 3 classes: normal with 266 images, benign with 891 image data, and malignant class with 421 image data.

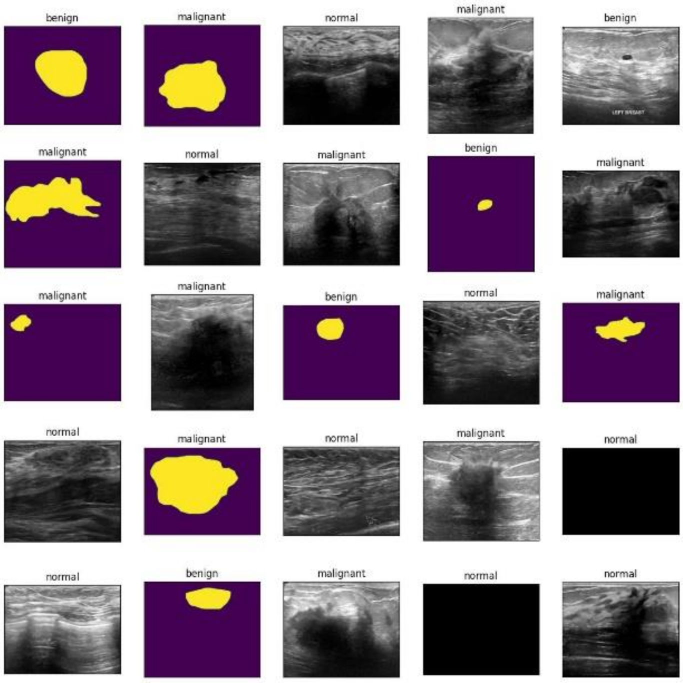

Figure 2. Examples of images in the dataset

Pre-Processing

In this process, data cleaning is carried out which is used to prepare data [26] before being applied to the classification model. The clean process is done to normalize the data, clean file names and strings that contain characters that are unnecessary or interfere with the analysis process. In addition, image resizing is done so that all datasets use img size format with a value of 128, then the data is initialized as an array for the model training process.

Classification and Prediction Methods

Before classification is carried out to predict disease, the dataset is split to divide into testing data and training data. In addition, pre-processing of the data is also carried out, then split data produces a dataset with a 15% testing data weight, consisting of 663 training data and 117 testing data, each of which has a size of 128x128 pixels and 3 channels (RGB). In addition, there are 3 target classes in the dataset that have been converted into one-hot encoding format. The model used is ResNet50 to classify the dataset. Model building is initialized with several parameters, and uses several layers to support the model. After the ResNet50 model is built, the fine tuning stage is performed. The model uses a number of iterations (epochs) of 30 and early stopping is applied to prevent overfitting.

Fine Tuning Method

Fine Tuning has several uses, in prediction the goal can be to refine the model created such as the prediction layer [27]. Model Fine Tuning works by improving the accuracy performance of given data that has been tuned/resolved with the base model [28]. The mathematical formulas used for fine-tuning are usually derived from conventional neural network training algorithms, such as using loss functions. The following is the use of Cross Entropy Loss or Negative Lg Likelihood in Eq 1.

$$\textit{Fine tuning with loss function} = -(y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)) \quad (1)$$

The computation shows that when the real label is 1 (y(i) = 1), the second portion of the function disappears, but when it is 0 (y(i) = 0), the first part disappears. It simply multiplies the log of the ground truth class's actual prediction probability. Fine tuning parts of the loss function, specifically cross entropy loss, severely penalizes confident but incorrect predictions. The use of fine tuning is intended to improve the performance of the model.

Evaluasi Model

In this research, the process uses the python language model in google colab. Evaluating the performance of the segmentation algorithm can be seen by looking at the evaluation metric score [29]. An example of Evaluation metrics calculation is shown in Eq.2 – Eq. 5

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad [30] \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad [30] \tag{3}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \times 100\% \quad [30] \tag{4}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad [29] \tag{5}$$

In the process of using CNN with ResNet50, several layers are used, shown in Figure 3.

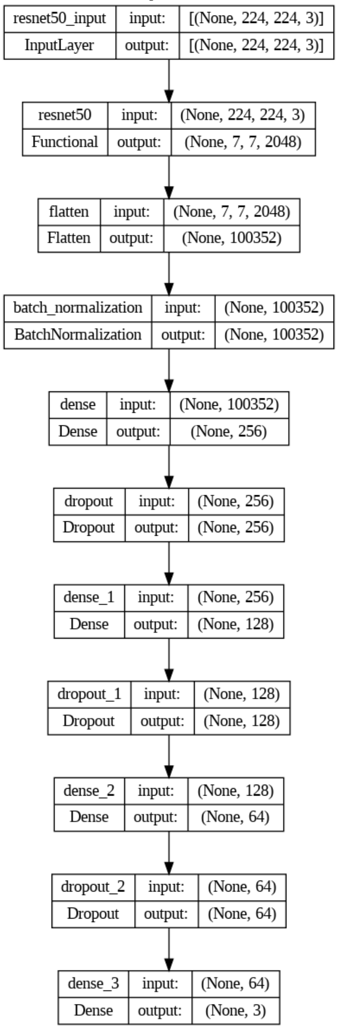

Figure 3. ResNet50 model layer structure

These are the layers used in the research process . The layers in the CNN (Convolutional Neural Network) algorithm have roles and benefits that support the selection of relevant features and produce high performance [31].

RESULTS AND DISCUSSION

The results of model training using ResNet50 that has been fine-tuned by applying early stopping produce reliable results in answering research problems. Using the first convolution layer in the ResNet50 model and retrieving the filter weights from that layer. Then, several filters will be displayed in Figure 3 according to the number of filters found.

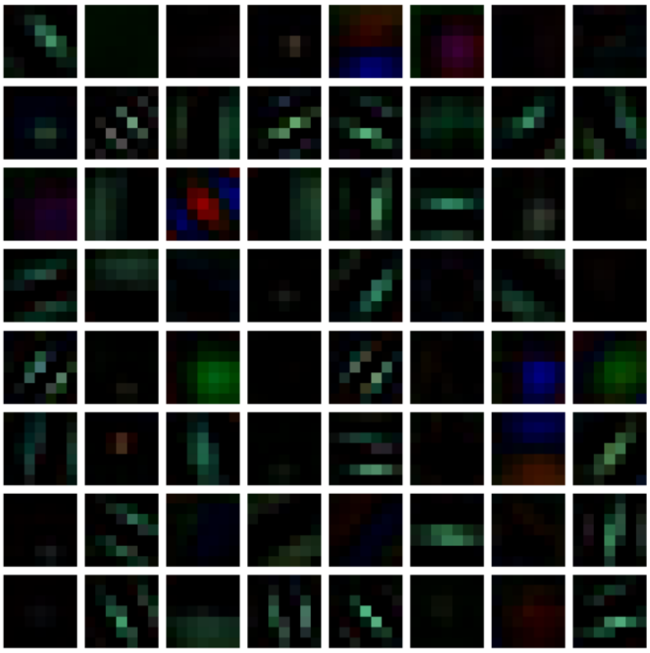

Figure 4. Multiple filter display of the first convolution layer in the ResNet50 model

The filter of the first convolutional layer in the ResNet50 model extracts the features of visual features, and has a role in breast cancer image processing in convolutional neural networks (CNN). The filter identifies in image processing and recognizes patterns that can be indicative of breast cancer, such as areas of high density, abnormal texture, changes in size and shape.

Model evaluation such as accuracy, precision, recall, and other metrics are used to describe the performance of the trained model. The following model training results are shown in Table 1 and Figure 5 using ResNet50 that has been fine-tuned with Early Stopping.

Table 1. Model training results

Training Model	Accuracy	Precision	Recall	F1 Score
Training set	96,07%	96,11%	96,07%	96,03%
Test set	93,16%	93,11%	93,16%	93,09%

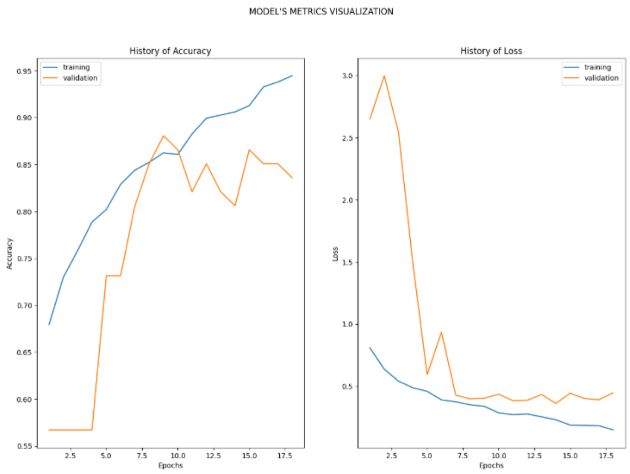

Figure 5. Training Models Metrics Visualization

In the output, it can be seen that at the 15th epoch, the training was stopped before reaching the specified number of epochs because the Early Stopping condition was met, namely val_loss which did not improve during the 'patience' epoch (in this case 10 epochs). Then, the model evaluation is performed on the training, and test set, which is indicated by accuracy (acc), precision, F1 Score and Recall.

Furthermore, the fine tuning added 3 dense layers and trained the model with Early Stopping for 10 epochs which are represented in Table 2 and Figure 6.

Table 2. Model test results

Fine Tuning Method	Accuracy	Precision	Recall	F1 Score
Training set	96,53%	96,56%	96,53%	96,49%
Test set	**96,58%**	**96,59%**	**96,58%**	**96,54%**

The output shows the model evaluation results on the training and test sets after training with fine tuning. The performance improvement can be seen in the accuracy values and other metrics depicted in Figure 6.

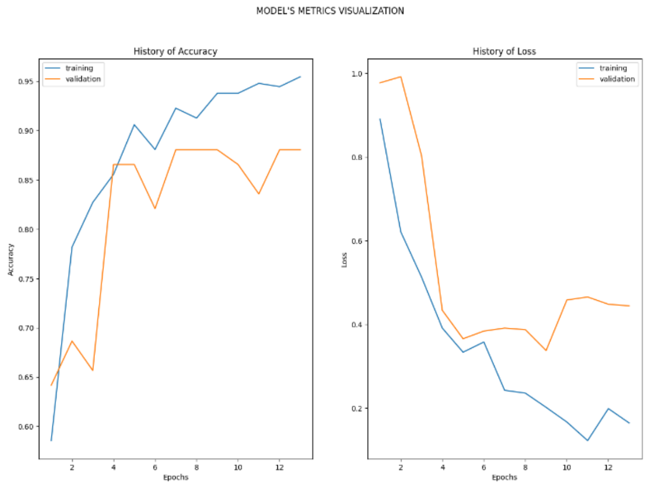

Figure 6. Models Metrics Visualization

Although the training data visualization is higher than the validation data, this is not overfitting, because the epoch performs early stopping at the 10th epoch and the graph shows the visualization for all epochs. Early stopping here stops training the model (training) before reaching full convergence, with the aim of preventing overfitting and speeding up training time.

Furthermore, to evaluate the prediction results of the classification model, the confusion matrix is used. To see the extent to which the model is able to classify data correctly and identify errors that may occur. The visualization is shown in Figure 5 below.

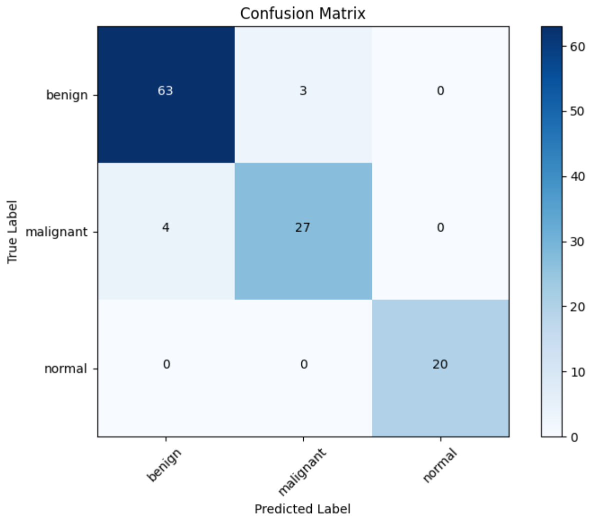

Figure 7. Confusion Matrix

In the given confusion matrix, the y-axis row represents the actual labels, namely benign, malignant and normal. Meanwhile, the X-axis represents the predicted labels. It can be seen that the model has a high level of accuracy, especially in predicting the benign and malignant classes. There are 63 correct benign predictions and 27 correct malignant predictions. However, there were some errors in prediction, with 3 benign predictions misclassified as malignant and 4 malignant predictions misclassified as benign. For the normal class, the model predicted perfectly without any errors. these results show that the model provides good results in classifying and predicting

To find out the comparison of the resulting model, a comparison was made with previous research by selecting one of the tests conducted on the same dataset. The comparison results are shown in Table 3.

Table 3. Performance comparison

Comparison	Algorithm	Accuracy
In [18]	Convolutional Capsule Network	87%
In [14]	Random Forest	92,40%
In [21]	BCD-Net	93.97%
In [22]	SVM + ResNet50	94,7%
Proposed method	**CNN + ResNet50**	**96.58%**

CONCLUSION

It is concluded that the proposed new model for CNN ResNet50 classification supported by Fine-Tuning method has good performance in predicting breast cancer. The model achieved an accuracy of 96.58% which shows a high degree of accuracy in classifying breast image images into benign, malignant and normal classes. However, there are some prediction errors that need to be considered. Therefore, further improvement in the performance of the ResNet50 CNN model and more in-depth evaluation are needed to ensure reliability and accuracy in breast cancer detection.

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