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Mass classification of breast cancer using CNN and faster R-CNN model comparison

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Abstract
Threat of breast cancer is a frightening type and threatens the female population worldwide. Early detection is preventive solution to determine cancer diagnosis or tumors in the female breast area. Today, machine learning technology in managing medical images has become an innovative trend in the health sector. This technology can accelerate diagnosing disease based on the acquisition of accuracy values. The primary purpose of this research is to innovate by comparing two deep learning models to build a prediction system for early-stage breast cancer. This research utilizes Convolutional Neural Network (CNN) sequential models and Faster Region-based Convolutional Neural Network (R-CNN) models that can determine the classification of normal or abnormal breast image data, which can determine the normal or abnormal classification of breast image. The dataset's source in this study came from the Mammographic Image Analysis Society (MIAS). This dataset consists of 322 mammogram data with 123 abnormal and 199 normal classes. The experimental results of this study show that the accuracy of the CNN and R-CNN models in image classification are 91.26% and 63.89%, respectively. Based on these results, the CNN sequential model has better accuracy than the Faster R-CNN model, because it does not require unique characteristics to detect breast cancer.

1. Introduction

Cancer is the most severe disease because it can threaten the human population worldwide [1][2]. Cases of this disease in Indonesia have increased from 1.4 per 1,000 in 2013 to 1.79 per 1,000 in 2018. Women's breast cancer cases are 42.10 per 100,000 population with an average death rate of 17 per 100,000 [3]. Meanwhile, data from the World Health Organization (WHO) Global Burden of Cancer Study (Globocan) recorded that the total cases of breast cancer in Indonesia in 2020 reached 396,914 with the total deaths were 234,511 cases [4]. Therefore, early detection is the solution and the reason for developing a system to diagnose cancer or tumours in the female breast area.

Based on these problems, several solutions have been carried out by researching to identify imaging biomarkers of breast cancer using multiparametric magnetic resonance and histogram analysis of all tumors or lumps [5]. Zebari et al. examined the identification of cancer through segmentation in the breast and chest muscles using thresholding and Machine Learning (ML) techniques [6]. Punithavathi and Devakumari made detection of breast lesions with an extraction process based on the Gray Level Co-occurrence Matrix (GLCM) feature. Khan et al. perform machine learning-based comparative analysis for breast cancer prediction [7]. Farhan et al. analyze breast cancer texture using LBP, HOG, and GLCM techniques [8].

Another research with a Computer-Aided Diagnosis (CAD) system that can automatically generate optimized algorithms for training machine learning in the classification of malignant and benign breast cancer [9][10]. Therefore, this study offers a breast cancer prediction system with deep learning. The main objective of this study is to propose deep learning as an early detection innovation. The innovation step in this research is to compare two models, namely CNN sequential model and Faster R-CNN, to classify normal or abnormal images based on breast area objects[11][12][13]. The use of the CNN model aims to deep learning image based on datasets. The Faster R-CNN model for deep learning, specifically on breast cancer image of predicts real-time.

The output of this research is a system that can predict normal and abnormal classification [14]. Abnormal classification is a breast condition with a lump or suspicious area requiring further clinical examination with a specialist [15]. The examination serves to identify suspicious areas such as tumors or cancer [16]. This research helps radiologists and specialists accelerate the disease diagnosis process based on the acquisition of accuracy values.

2. Research Method

This research uses the deep learning method. Deep learning is a machine learning subfield with a network structure like the human brain [17][18][19]. The difference between deep learning and machine learning is in data management performance. Deep learning can manage an increasing amount of extensive data and solve a problem, while machine learning optimally processes small amounts of data [20][21]. The use of deep learning in this study can adapt to updating data and recognizing disease functional and structural characteristics [22]. This study deploy of deep learning utilizes CNN sequential models and Faster R-CNN. CNN processing sequential model in python, while Faster R-CNN utilizes the framework from Tensorflow as framework of an open-source deep learning framework with a library to perform computational calculations with high performance [17]. The model is based on CNN [23], which acts as a backbone and produces an algorithm that can detect objects to perform classification quickly [24].

CNN and R-CNN models are used to detect, determine, and classify breast cancer image. The image data in this study were sourced from the MIAS dataset (https://www.kaggle.com/code/lemonweed/cancer-classification/data) [25]. The MIAS dataset contains information about breast cancer which consists of 322 images with details of 123 abnormal and 199 normal. This dataset is private, so no detailed information is available, including age, never been pregnant, overweight, giving birth over the age of 30 years, menopause, menstruating age <12 years, or radiation from radiotherapy. However, this dataset provides information on classifying normal, abnormal, benign, and malignant images. This study focuses on the classification of normal and abnormal. Normal classification describes the condition of a healthy breast area. Abnormal classification is a condition of the breast area that has swelling or something suspicious, so it requires further examination to determine the tumor or cancer with a benign or malignant classification.

The proposed approach in this study utilizes python programming to run the CNN model and the TensorFlow framework for Faster R-CNN. The proposed approach of the CNN model aims for deep learning of image based on datasets [26]; Faster R-CNN functions for early prediction of breast cancer through detecting and classifying cancer objects in the chest and breast muscles. The detection system in this research focuses on labeling each image so that the key indicator of the recognition process is the accuracy value. Faster R-CNN is the main algorithm for detecting targets (breast cancer objects) in deep learning because it has a substantial advantage in inaccuracy. The Faster R-CNN algorithm has a Regional Proposal Network structure to generate target areas and make target positioning very precise. Therefore, Faster R-CNN is the primary research algorithm for its efficacy in detecting disease points [13]. The stages of the early breast cancer prediction system is shown in Figure 1.

Figure 1. The Sages of CNN and Faster R-CNN Implementation

Figure 1 provides information on the seven stages of how the application of the breast cancer early prediction system works in this study. The first stage is through the collection of the MIAS dataset containing image from breast cancer. The second stage is preprocessing through data augmentation, which expands the data set to improve model performance by producing various forms of image variations. This stage can enrich the sample data in the training folder.

In the third stage, data annotation plays a key role in labeling the position and class of disease object areas on the image. This data also serves to detect multiclass objects. The fourth stage divides the data as needed, namely the training and testing data folder. The training folder acts as an independent variable and the testing folder as a fixed variable. The fifth stage includes two processes: train with Faster R-CNN and trained model. The Faster R-CNN process trains the recognition of image objects that produce loss values and the loss values become error parameters in image recognition. Calculation of loss value during training using Equation 1.

$$L(\{pi\},\{ti\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(pi,pi^*) + \lambda\frac{1}{N_{reg}}\sum_i pi * L_{reg}(ti,ti^*) \tag{1}$$

Equation 1 where i is the anchor index, pi is the predictive probability of the anchor, pi^* as a fundamental truth label, ti acts as a vector representing the four-parameter coordinates of the prediction bounding box, and ti^* is a ground-truth box associated with the positive anchor. Representative classification and regression loss with symbol L_{cls} and L_{reg}. In addition, it serves as a balancing parameter. Each parameter is normalized by N_{cls} and N_{reg}. It is weighted by λ. The second process is the trained model, which calls the labelmap function and recognizes image based on labels.

The label is to predict disease so that the system will measure the recognition accuracy based on the predicted classification results.

The sixth stage is the system testing in detecting, recognizing, and classifying breast cancer from image. The finally stage acts as a process of evaluating system performance in detecting and classifying breast cancer. The evaluation involved system performance and accuracy scores in breast cancer recognition. The following is the Equation 2 for the accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

The measurement of the classification accuracy value is based on Equation 2 with a TP (True Positive) value which is the truth value of a prediction. The TN (True Negative) means the predicted value that is rejected in a positive state. The FP (False Positive) is the identification of the wrong class value, while the FN (False Negative) acts as the class value that is rejected in a negative state [17]. The application of the proposed approach in research uses a Ryzen 5 4000 series hardware processor, 4GB NVIDIA GeForce GTX1650Ti GPU, 16GB RAM, and Windows10 64 bit.

3. Results and Discussion

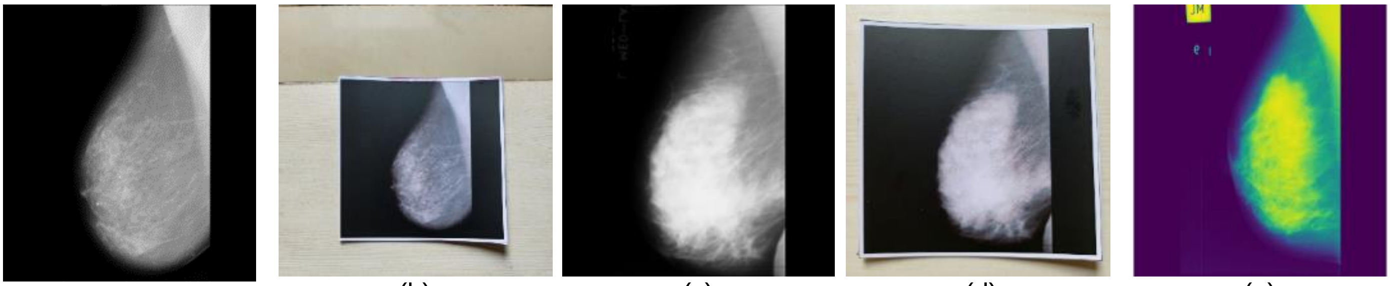
This section describes the results of applying the proposed approach to breast cancer. This study utilizes datasets as research subjects to evaluate the performance of the proposed approach, while breast cancer is the object of research.

3.1 Online Dataset MIAS Breast Cancer

The total MIAS dataset in this study is 322 images. The data consists of two categories, namely normal and abnormal breast X-rays. This study took 15 normal and 15 abnormal, which served as the primary model of 220 data for training and 72 image for testing deep learning capabilities.

3.2 Data Augmentation

This stage multiply the training data from 140 to 340 images. The purpose of multiplying the data is to provide a more comprehensive reference for training data. This study prints breast X-ray image and take pictures using a smartphone camera at a distance of 5 cm, 10 cm, and 15 cm. The image-taking process is to test the system's success in detecting and classifying into normal and abnormal breast categories. The data augmentation process is shown in Figure 2.



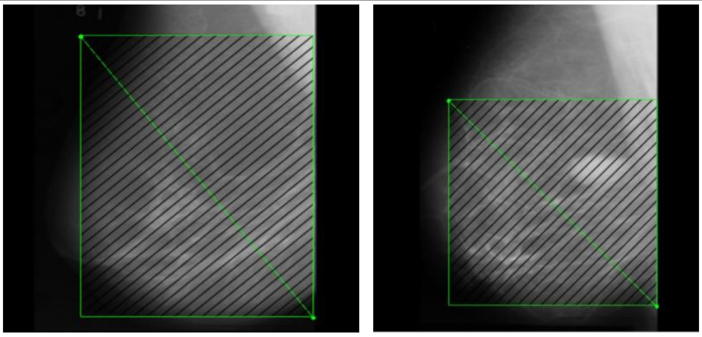
(a) (b) (c) (d) (e)

Figure 2. Data Augmentation Process of Breast Image: (a) Normal, (b) Portrait with a Distance of 15 cm, (c) Abnormal, (d) Portrait with 5 cm Distance, (e) with Python Processing

Figure 2 provides an overview of the process of multiplying training data in this study. Points a and c show the ideal data from the dataset, while points b, d, and e are the results of augmentation data processing. This stage provides capital to train the system to recognize image, especially breast cancer.

3.3 Data Annotation

This stage processes image by labeling normal and abnormal based on information from the MIAS breast cancer dataset. The labeling of the image is shown in Figure 3.



(a) (b)

```
label = []
for i in range(len(info)):
    if info.CLASS[i] != 'NORM':
        label.append(1)
    else:
        label.append(0)
label = np.array(label)
print(f"Cant. Imagenes: {len(label)},
Normales = {len(label)-np.sum(label)},
No normales= {np.sum(label)}")
```

(c)

Figure 3. Annotation Data: (a) Normal Breast, (b) Abnormal Breast, (c) Normal and Abnormal Breast with Python

Figure 3 shows the process of labeling breast X-ray image based on the dataset. Points a and b give abnormal or normal labels to specific image. Point c represents labeling automatically using the python programming language. The labeling of points a and b is for the Faster R-CNN model, while point c is for the deep learning CNN model. In addition, the labeling process aims to identify the particular characteristics of the image.

3.4 Data Partition

The images is allocated between the model and training data at this stage. The placement of the model image is in the test folder, while the training image is in the train folder. The two folders each have data label for each image. Furthermore, this stage manages the label results and generates label data in CSV format. The data contains information for each image and becomes a reference for deep learning systems.

3.5 Training Data and Model

The system performs data and model training to recognize the image on the breast cancer dataset at this stage. The CNN model data training process is shown in Figure 4.

```
Epoch 00020: val_loss improved from 0.23965 to 0.23417, saving model to ./
Epoch 21/100
443/443 [==============================] - 119s 269ms/step - loss: 0.1865 - accuracy: 0.9253 - val_loss: 0.2226 - val_accuracy: 0.9149

Epoch 00021: val_loss improved from 0.23417 to 0.22259, saving model to ./
Epoch 22/100
443/443 [==============================] - 119s 268ms/step - loss: 0.1798 - accuracy: 0.9292 - val_loss: 0.2299 - val_accuracy: 0.9121
Restoring model weights from the end of the best epoch.

Epoch 00022: val_loss did not improve from 0.22259
Epoch 00022: early stopping
```

Figure 4. CNN Training Data Process

Figure 4 shows that the training process stops at the 22nd epoch or step. The process stopped because CNN could not minimize the total loss value of 0.22259; Next is the Faster R-CNN model training, which runs for three hours with 62,707 steps. The training log of Faster R-CNN data is shown in Figure 5.

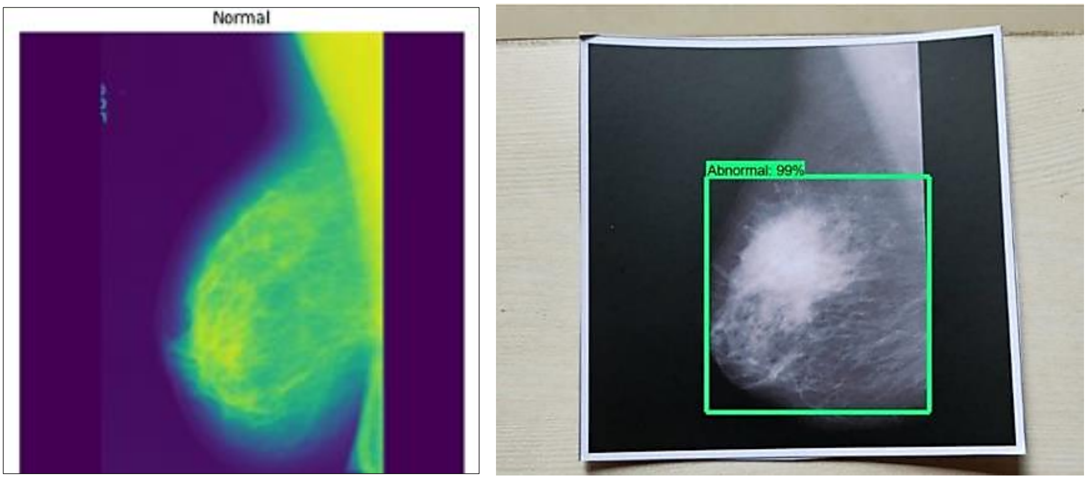
```
I0513 17:35:59.986310 19516 learning.py:507] global step 166: loss = 1.5722 (0.240 sec/step)
INFO:tensorflow:global step 167: loss = 1.0396 (0.268 sec/step)
I0513 17:36:00.259372 19516 learning.py:507] global step 167: loss = 1.0396 (0.268 sec/step)
INFO:tensorflow:global step 168: loss = 1.4010 (0.248 sec/step)
I0513 17:36:00.512096 19516 learning.py:507] global step 168: loss = 1.4010 (0.248 sec/step)
INFO:tensorflow:global step 169: loss = 0.7894 (0.286 sec/step)
I0513 17:36:00.805143 19516 learning.py:507] global step 169: loss = 0.7894 (0.286 sec/step)
```

Figure 5. Faster R-CNN Training Data Process

Figure 5 shows the image data training process, step 169, with a loss of 0.7894. The comprehensive training data with the Faster R-CNN model obtained a total loss of 0.0131. Based on the results of the two models, the next step is to test the system.

3.6 Disease Detection and Classification

This stage describes the system test results from the CNN and Faster R-CNN models for detection to image data classification. Testing the proposed approach system uses image in real-time as shown in Figure 6.



(a) (b)

Figure 6. System Testing: (a) CNN on Normal Breast Image, (b) Faster R-CNN on Abnormal Breast Image

Figure 6 shows the results of the system testing process on the CNN and Faster R-CNN models in detecting breast cancer images. Point a is the result of CNN model detection with normal image class. Point b is the result of real-time Faster R-CNN detection, which detects that the image class is abnormal—the process of detecting images in real-time using a smartphone camera.

3.7 Performance Evaluation

This stage describes the results of the evaluation and analysis of the performance of the proposed approach system in detecting and classifying breast cancer. The performance results in this stage consist of two models, namely the CNN model and the Faster R-CNN model. The accuracy and total loss of the CNN model is shown in Figure 7.

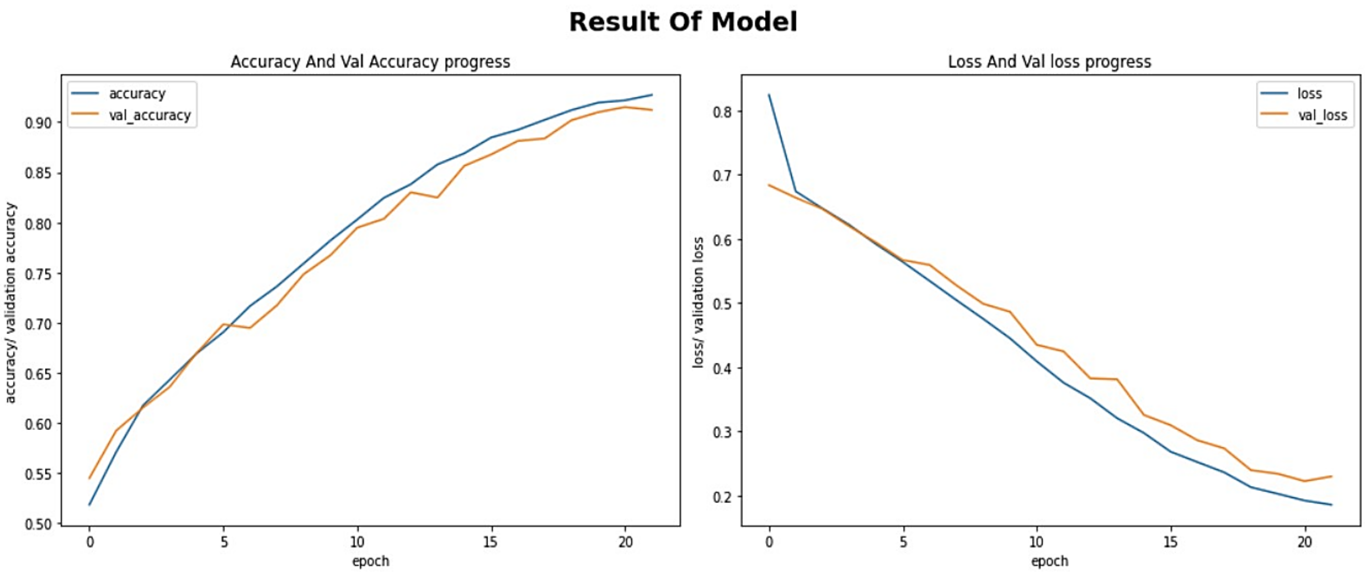


Figure 7. CNN Model System Performance

Figure 7 provides information on the performance of the CNN model system in detecting and classifying breast cancer image. The performance results include the value of accuracy and loss during the image data training process. The amount of the value obtained a percentage of >90%, and the value of the loss reached a percentage of 0.2; Based on that CNN sequential model can detect differences in the image of normal and abnormal breast cancer. One of the essential factors in achieving >90% accuracy in sequential models is presenting labels on the image. However, presenting the CNN label is general and does not use the particular features of an image. The total loss performance of the Faster RCNN model system is shown in Figure 8.

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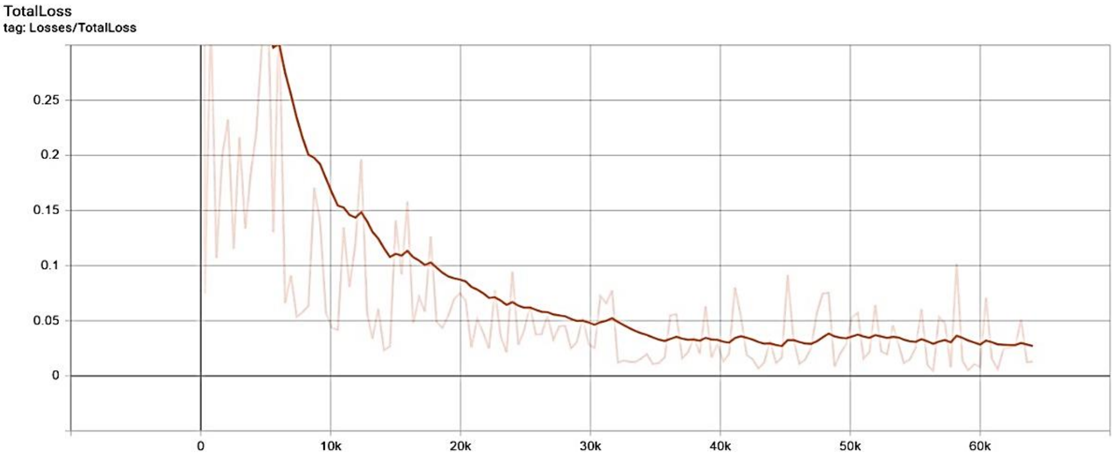

Figure 8. Total Loss System Performance of Faster R-CNN

Figure 8 shows the total loss on the Faster R-CNN model to process image data training. The graph provides information on the amount of the total loss value < 0.05; the loss is the process of recognizing image data from losses > 0.25 to < 0.05; The recognition of the data is based on labelling so that the Faster R-CNN model tries to determine the particular characteristics of the image. The performance of Faster R-CNN classification loss is shown in Figure 9.

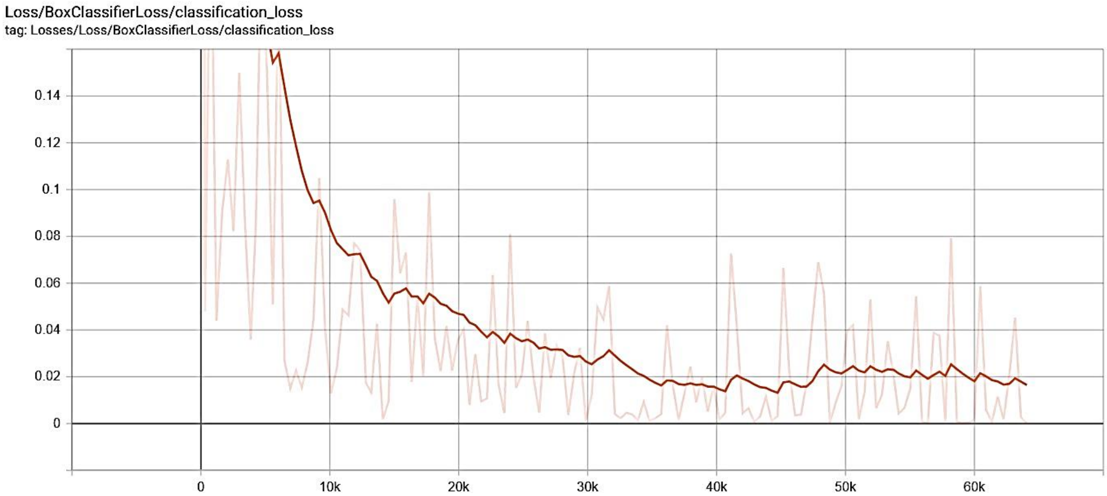

Figure 9. Performance Classification Loss of Faster R-CNN

Figure 9 provides information on the performance classification loss system for image data to detect breasts in normal or abnormal classes (breast cancer). The graphic image shows that the loss classification value is in the range of ±0.02 during the image data training process. The results of this performance provide an overview of the performance of the Faster R-CNN model in determining breast image based on labelling and in particular. The results of the comparison evaluation of the two deep learning models are shown in Table 1.

Table 1. Evaluation Results of CNN and Faster R-CNN

Model	Information	Accuracy (%)	Total Loss
CNN	Deep Learning	91.26	0.2326
Faster R-CNN	Deep Learning	63.89	0.0131

Table 1 provides information on the evaluation results of the CNN and Faster R-CNN models. The accuracy of the CNN model is 91.26%, while Faster R-CNN is 63.89%. The Faster R-CNN model's remaining 36.11% accuracy rate is the FP and FN values. This study determines the accuracy value of Faster R-CNN based on real-time testing and mathematical calculations using Equation 2. Details of the accuracy values for testing the Faster R-CNN model with 72 samples of image data are TP = 27, FP = 9, TN = 19, and FN = 17. The difference in accuracy occurs because of the different labeling processes. The CNN model gives general labeling to image, while the Faster R-CNN model labels image specifically so that it demands special characteristics of the image to recognize and produce higher accuracy

[15][27][28]. Another factor that affects the accuracy of the Faster R-CNN model is the resolution of the smartphone camera and the breast cancer image. In this study, the image has three colors only, namely black, white, and gray after normalization. The visualization of image data on the Faster R-CNN system is shown in Figure 10.

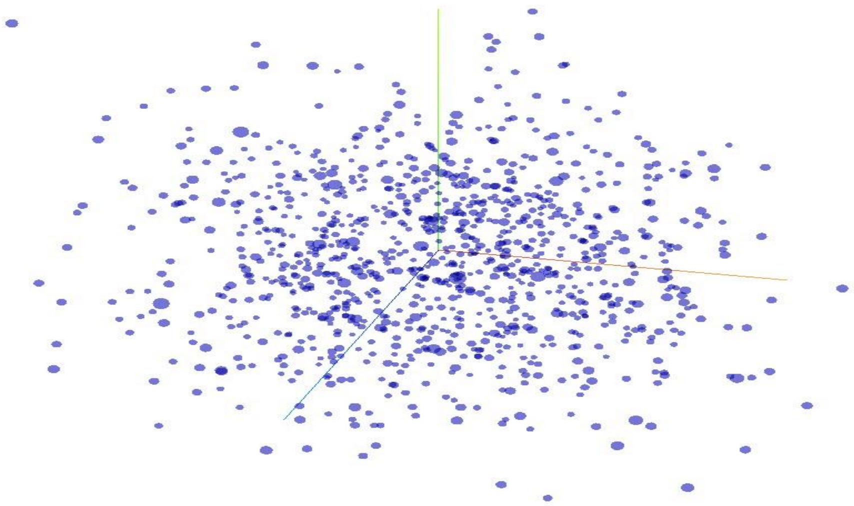

Figure 10. Visualization of Image Data on the Faster R-CNN

Figure 10 provides an overview of the distribution of breast cancer image data, including normal and abnormal categories. These results will be different if the use of images that have many color compositions as in the study [13]. The comparison the results of this study with previous studies is shown in Table 2.

Table 2. Comparison of Accuracy Results for Breast Cancer

Reference	Model	Information	Accuracy (%)
Fadhil et al. [25]	CAD	Machine Learning	93.60
Dawngliani et al. [29]	Random Forest	Machine Learning	97.13
Khan et al. [7]	Decision Tree	Machine Learning	94.73
Marsilin [30]	K-Nearest Neighbor	Machine Learning	85.00
Khan et al. [7]	Logistic regression	Machine Learning	98.60
Proposed Approach	CNN	Deep Learning	91.26
Proposed Approach	Faster R-CNN	Deep Learning	63.89

Table 2 provides information on comparing the results of the accuracy values in this study with previous studies. Fadlil et al[25]. using The Mammographic Image Analysis Society (MIAS) dataset with the computer-aided detection method, and the accuracy is 93.60%. Dawngliani et al[29]. using dataset sourced from Mizoram Cancer Institute from 2009-2016. Data processing uses data mining, namely Random Forest with an accuracy of 97.13%. Khan et al[7]. using the Wisconsin Breast Cancer Diagnostic (WBCD) dataset. Data processing uses machine learning methods which are logistic regression, decision tree, and others. The results of this study obtained a logistic regression accuracy value of 98.60% and a decision tree of 94.73%. Marsilin researched the classification of breast cancer using the query image with the database of breast cancer images[30]. The research method uses content-based image retrieval (CBIR) and KNN Classifier, so the results have an accuracy of 85.00%. The proposed approach of this research using the CNN deep learning method achieved an accuracy rate of 91.26% when recognizing MIAS breast cancer data, while the Faster R-CNN model achieved an accuracy rate of 63.89% in recognizing image data on the MIAS breast cancer dataset in real-time. Therefore, the application of Faster R-CNN in the proposed approach of this research is not optimal due to the limited color in the breast cancer image.

4. Conclusion

This study tries to conduct experiments by building an early detection system for breast cancer through deep learning technology. The application of deep learning in this study runs with two models, namely CNN and Faster R-CNN. Both models have their respective advantages and disadvantages. The CNN model performs the general image data labeling process by automating the python program. Labeling the Faster R-CNN model runs specifically on each image data to provide a more profound introduction to the system. This deeper introduction is intended so that the system can determine the particular characteristics of the image data. The hope of applying the Faster R-CNN model in this study is to achieve accuracy and benefit for radiologists and specialists. Suggestions for further research by improving the image of breast cancer [7].

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