Development of AI Models from Mammography Images for Early Detection of Breast Cancer

Nurbaiti[1], Eka Putra Syarif Hidayat[2], Khairil Anwar[3], Dudung Hermawan[4], Salman Izzuddin[5]
[1,2,3]Poltekkes Kemenkes Jakarta II
[4]Universitas Islam Asy syafiiyah
[5]Universitas Mercu Buana
E-mail: [1]*nurbaiti@poltekkesjkt2.ac.id*, [2]*eka.putra@poltekkesjkt2.ac.id*, [3]*khairil.anwar@poltekkesjkt2.ac.id*, [4]*dudung6234@gmail.com*, [5]*salmanizzu.edu@protonmail.com*

Coresponden Author: *nurbaiti@poltekkesjkt2.ac.id*

Diterima Redaksi: 01 Desember 2023 Revisi Akhir: 22 Februari 2024 Diterbitkan Online: 12 Maret 2024

Abstrak – *deteksi dini kanker payudara dengan bantuan komputer telah berkembang sejak dua dekade lalu. Kecerdasan buatan menggunakan metode convolutional neural network (CNN) berhasil memprediksi gambar mamografi dengan tingkat akurasi tinggi serupa dengan pembelajaran otak manusia. Potensi model AI memberikan peluang untuk mengenali kasus kanker payudara dengan lebih baik. Penelitian ini bertujuan untuk mengembangkan model AI dengan CNN menggunakan dataset publik DDSM dengan jumlah sampel 1871, terdiri dari 1546 gambar untuk pelatihan dan 325 gambar untuk pengujian. Model AI ini memberikan hasil prediksi dengan tingkat akurasi yang berbeda-beda. Peningkatan akurasi model AI dapat dilakukan dengan cara meningkatkan kualitas gambar sebelum proses pemodelan, menambah jumlah dataset, atau melakukan proses iterasi yang lebih mendalam agar model AI dengan CNN memiliki tingkat akurasi lebih baik*

Kata Kunci *— convolutional neural network, deteksi dini, kanker payudara*

Abstract – *early detection of breast cancer with computer assistance has developed since two decades ago. Artificial intelligence using the convolutional neural network (CNN) method has successfully predicted mammography images with a high level of accuracy similar to human brain learning. The potential of AI models provides opportunities to spot breast cancer cases better. This research aims to develop AI models with CNN using the public DDSM dataset with a sample size of 1871, consisting of 1546 images for training and 325 images for testing. These AI models provided prediction results with different accuracy rate. Increasing the accuracy of the AI model can be done by improving the image quality before the modeling process, increasing the number of datasets, or carrying out a more profound iteration process so that the AI model with CNN can have a better level of accuracy.*

Keywords *— breast cancer, convolutional neural netwotk, early detection*

1. INTRODUCTION

The Breast cancer is the most common cancer found in women worldwide and causes many deaths. New cases of breast cancer in 2020 are estimated to reach 19.3 million, and cases are estimated to increase by 47% to reach 28.4 million in 2040 [1][2]. Early discovery of breast cancer cases can provide good therapeutic results and reduce death rates due to breast cancer [3]. When breast cancer cases are discovered early and localized, the 5-year survival rate reaches 99% [4].

Breast cancer examination can be done with various instruments such as mammography, ultrasound, tomography, and magnetic resonance. Mammography is the standard examination for breast cancer and is recommended for early detection of this disease [5].

Mammogram is a special radiological examination practical for early breast cancer detection. This examination uses exposure to X-ray radiation on breast tissue and records it on the film's surface. Mammogram results can show abnormal breast tissue changes that may not yet be physically visible or cause no symptoms [6]. Currently, the conventional mammogram method using SFM (screen-film mammography) has developed into digital mammography using full-field digital mammography (FFDM) [7].

Breast cancer screening in groups of women who are not at risk can be done every two years, while it needs to be done every year for women who are at risk. Some risks associated with breast cancer are women, age, family history of this disease, hormone therapy, history of early menstruation at a very young age (early menarche), late menopause, history of radiation exposure, and history of neoplastic disease, previous, obesity, and others [8].

Efforts to detect early breast cancer widely in the female population require a lot of energy and time. Suppose we adopt the breast cancer screening method by reading mammography by two radiologists (double-reading) as is the health standard in Europe and Asia. In that case, this effort will increase health costs.[9][10].

On the other hand, screening carried out using mammography still leaves cases of breast cancer that cannot be recognized [11][12]. The ability of radiologists to interpret mammography varies— this challenge in finding breast cancer cases [13]. Various obstacles in the early detection of breast cancer encourage us to look at opportunities to use computer assistance to support the diagnostic process.

Current developments in new technology in deep learning algorithms provide new opportunities in radiology. One of them is deep learning, which allows object recognition or language recognition and interpretation through neural networks that work automatically using computer programming languages [14][15][16].

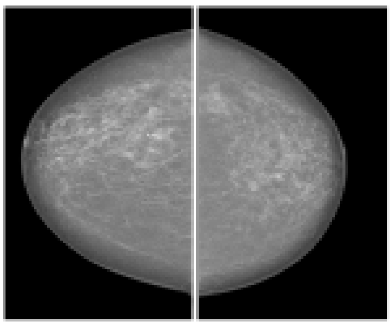
1.1. Deep Learning and Mammography Images

Mammography interpretation with deep learning programs has succeeded in improving mammography analysis. These results are useful for increasing accuracy and more effective breast cancer screening by reducing the clinical workload of doctors [17][18][19][20].

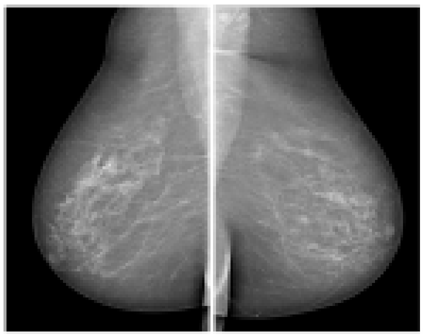
Breast cancer detection using computer-aided detection (CAD) mammography can help screen breast cancer in the community in conditions where there are not enough radiologists to analyze mammography or function as support in determining breast cancer diagnoses made by radiologists [21][22] [23][24]. A condition that needs to be watched out for is when many false negative mammography assessment results impact the results of detecting breast cancer cases in the community [25][26].

Developing deep learning mammography research with the emergence of public mammography datasets. The Digital Database for Screening Mammography (DDSM), the Mammographic Image Analysis Society (MIAS), and INbreast are some sources that provide digital mammography images. They contain a collection of mammography image data accompanied by supporting information and can be used for digital mammography image research with deep learning algorithms [27][28].

Various mammography database sources have varying information. In general, mammography datasets refer to standard mammography examination results, which consist of 4 images, namely two projections on each side of the breast, namely craniocaudal (CC), which is an image of the breast from top to bottom, and mediolateral oblique (MLO) which shows an oblique image of the breast or diagonal [29] as shown in figure 1(a, b).



1.a. Right and Left Craniocaudal (CC)
Mammography ImageS



1.b. Right and Left Mediolateral Oblique (MMO)
Mammography Images

Figure 1**.** Mammography Image (a,b) [30]

An essential stage in AI research using digital mammography is providing appropriate markers or labels (image annotation process). This label is used to provide appropriate characteristics of abnormalities that occur in breast tissue that will be identified by the AI model [30]. Abnormalities commonly seen in breast tissue are masses, calcifications, architectural distortion, and asymmetry [31][32][33] [34][35].

After labeling, the next stage is to classify digital imaging into the BIRADS category, as shown in table 1 [30] [36].

Table 1. Classification Using The BIRADS Method for Assessing Mammography Results

Category 0	Mammography: incomplete Ultrasound and MRI: incomplete
Category 1	Negative
Category 2	Benign
Category 3	Probably benign
Categoryi 4	Suspicious mammography and ultrasound: Category 4A: Indicates a low level of suspicion of malignancy Category 4B: Indicates a moderate level of suspicion of malignancy Category 4C: Indicates a high level of suspicion of malignancy
Category 5	Highly indicative of malignancy
Category 6	Biopsy-confirmed malignancy

The AI system can evaluate digital mammography (DM) like a radiologist. In one study, the AI model showed a higher area under the curve (AUC) of 61.4% compared to the radiologists involved [19][37][38][39].

1.1.1. Artificial Intelligence, Maschine Learning, and Deep Learning

AI is a part of computer science that enables computers and computer systems to perform functions that normally require human intelligence, such as the ability to understand natural language, make decisions, reason and act based on knowledge. The main idea of developing AI is to build a systems that can carry out learning process and act like humans [40].

1.1.2. Machine Learning (Machine Learning)

Machine learning is a subfield of AI that focuses on developing algorithms that allow computers to learn from data and make predictions or decisions based on understanding that data. In machine learning, models or algorithms are developed to understand patterns and relationships in data so that the models can be used for tasks such as classification, regression, clustering, and others. Machine learning is divided into several types, including supervised learning, unsupervised learning, and reinforcement learning (incentive-based learning) [41].

1.1.3. Deep Learning (Learning in Artificial Neural Networks)

Deep learning is a specialized subfield of machine learning that uses deep artificial neural network architectures to process complex data. With deep learning, models can be developed that represent the work of brain neurons in layers to analyze complex data [42].

Convolutional Neural Network (CNN) is a specific type of deep learning with a deep learning network architecture specifically designed for image, image, or object processing tasks and language processing [40][38]. CNN mammography images. An illustration of the relationship between artificial intelligence, machine learning, and deep learning is shown in Figure 2 [40].

AI models with CNN have shown promising results in recognizing image patterns. The use of this model is increasingly popular in the field of radiology, including the detection of X-ray images in cases of tuberculosis [43] and breast tumors [44][42].

1.2. Development the AI Model

In developing the AI model, deep learning with CNN works hierarchically to construct an AI model that can deeply recognize patterns in mammography image data. CNN generally consists of layers that play a role in the AI model development process. Some layers that are generally involved in the process are [45]:

1.2.1. Input Layer

The input layer is the first layer in CNN that receives images or input data. The size of the input layer corresponds to the image's dimensions to be processed — for example, a color image measuring 224x224 pixels.

1.2.2. Convolutional Layer

This layer is the core of CNN. Each layer has a filter or kernel to extract features from the input image. The filter moves across the input image, performs convolution operations, and produces a feature image (feature map) containing information about the features found in the image. Multiple convolutional layers may exist in the model, each with different filters to identify different levels of features, ranging from edges to more complex features.

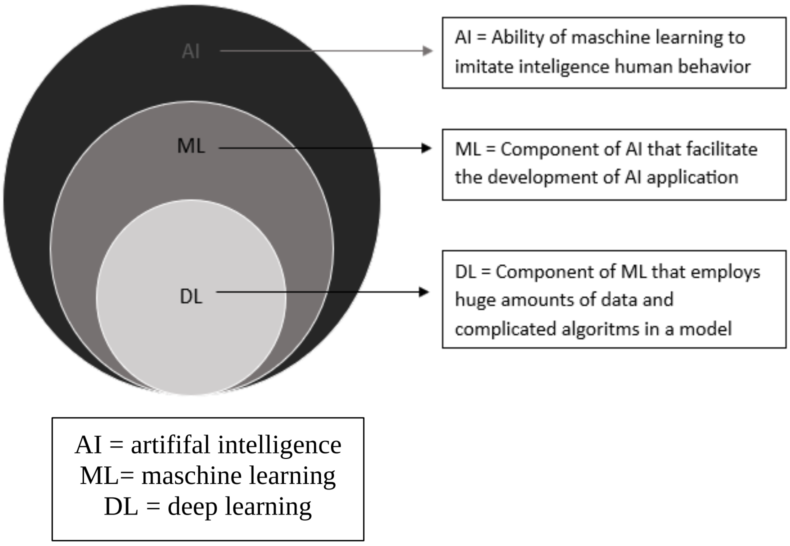


Figure 2. An illustration of the Relationship between Artificial Intelligence, Machine Learning, and Deep Learning [40]

1.2.3. Activation Layer

After the convolution operation, an activation function such as ReLU (Rectified Linear Unit) is implemented to each value in the feature map. This layer introduces non-linearity so the model can learn more, complex patterns in the data.

1.2.4. Pooling Layer

The pooling layer reduces the dimensions of the feature map by taking the maximum or average value from a group of values in a particular area. This process aims to reduce the number of parameters needed in the model, reduce overfitting, and make the feature representation more translation invariant.

1.2.5. Fully Connected Layer

This layer is located in most of the CNN and consists of whole neurons connected to all the neurons in the previous layer. Fully connected layers are used for decision-making and classification, turning increasingly abstract feature representations into classification probabilities or relevant output values.

1.2.6. Output Layer:

The outer layer is the CNN layer that produces the final output, which can be in the form of classification or regression values.

In developing an AI model with a Convolutional Neural Network (CNN), an iterative process is required, namely repeated steps taken to train and perfect the model. This process involves several cycles to optimize the model [46].

The process of developing an AI model involves the following iterative or iterative learning process, including:

a. Model Training (training): During the first iteration, the model gets training with the dataset containing images and the correct labels. The model will make an initial prediction based on its initial weights, and then the error between the prediction and the correct label is measured (usually using a loss function).

b. Validation: After the first iteration of training, the model is evaluated on different validation datasets to check its performance. The validation process assesses whether the model is good enough or requires further adjustments. If the validation result is not good, the model and architecture parameters will be adjusted to improve performance. In the next iteration, the above process is repeated in several cycles. At each iteration, the model learn continuesly from the training data and refine its representation of patterns in the data. This process includes identifying more abstract and complex features that may not be detected initially.

c. Model assessment (testing): After several iterations, the model can be tested on a never-before-seen test dataset to assess its performance in generalizing to new data. This process continues until the model reaches a sufficient level of performance in tasks such as object recognition or image classification. The number of iterations required may vary depending on the task's complexity and the training dataset's size. The heart of AI model development with CNNs is the process of iteration, enabling the model to continuously adapt and enhance its performance through learning from data.

1.3. AI Models with CNN

One research team built an AI algorithm model for breast cancer screening using CNN with mammography image samples from 270 patients. The research dataset consists of 200 data for training and 70 for testing. This model was developed to assess the risk of breast cancer in the coming years with an accuracy value of 71.4%. This AI model can potentially assess the risk of developing breast cancer in the short term when negative mammography screening results from patients [37].

This research develops an AI model with a convolutional neural network (CNN) using samples of breast ultrasound images with benign and malignant masses for training and testing the patients. Breast ultrasound examination supports mammography image results or sharpens the differentiation between benign and malignant lesions. This AI model's results were compared with radiologists' evaluation results. The AI model showed equivalent or even slightly better results than the doctors' review [38].

Mammography image samples were used in this research to develop an AI model with a convolutional neural network (CNN) that classifies benign and malignant mammography lesions. The data used in the research comes from the INbreast public dataset. The resulting AI model provides a high level of sensitivity in recognizing mammography images and classifying them into two categories (benign and malignant) [39].

2. RESEARCH METHOD

This research received research ethics permission from the Health Research Ethics Commission of Poltekkes Kemenkes Jakarta II Jakarta in 2023. This research was carried out to develop AI Models with a convolutional neural network (CNN) to classify mammography images into 5 BIRADS categories. Hopefully, the new AI models from this research will be able to assess mammography images with BIRADS classification. This research uses the public dataset downloaded via kaggle.com (https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset).

The data used was 1871, with image samples divided into two sets. The dataset for training is 1546 images, and the data for testing is 325. The images consist of 3 types: mammography image, cropped mammography image, and ROIs (region of interests) mask of mammography.

The research team developed AI models from existing image samples in this study. This dataset has shortcomings, including non-uniform image resolution. The research team used all available datasets. The images used are craniocaudal (CC) mammography images and Mediolateral Oblique (MMO) mammography images. The dataset already has labels for the mammography images.

The dataset is arranged in the BIRADS (Breast Imaging Reporting and Data System) score category format. The values in BIRADS are interpreted as follows: 1 (negative), 2 (clear findings), 3 (probably benign), 4 (suspicious abnormality), and 5 (highly suspicious or malignancy). The development of the AI model with CNN uses the Python programming language with three neural network layers: input layer, hidden layer, and output layer. This AI model uses the Adam optimizer and Stochastic Gradient Descent (SGD) to increase the model's accuracy [47][48].

The AI model output with CNN produces image interpretation in 5 BIRADS categories (1 - 5) and an assessment of the level of accuracy. The complete flow of the research activity is shown in figure 3, the conceptual design of AI model in figure 4, and configuration of CNN in the AI models in this study is in table 2.

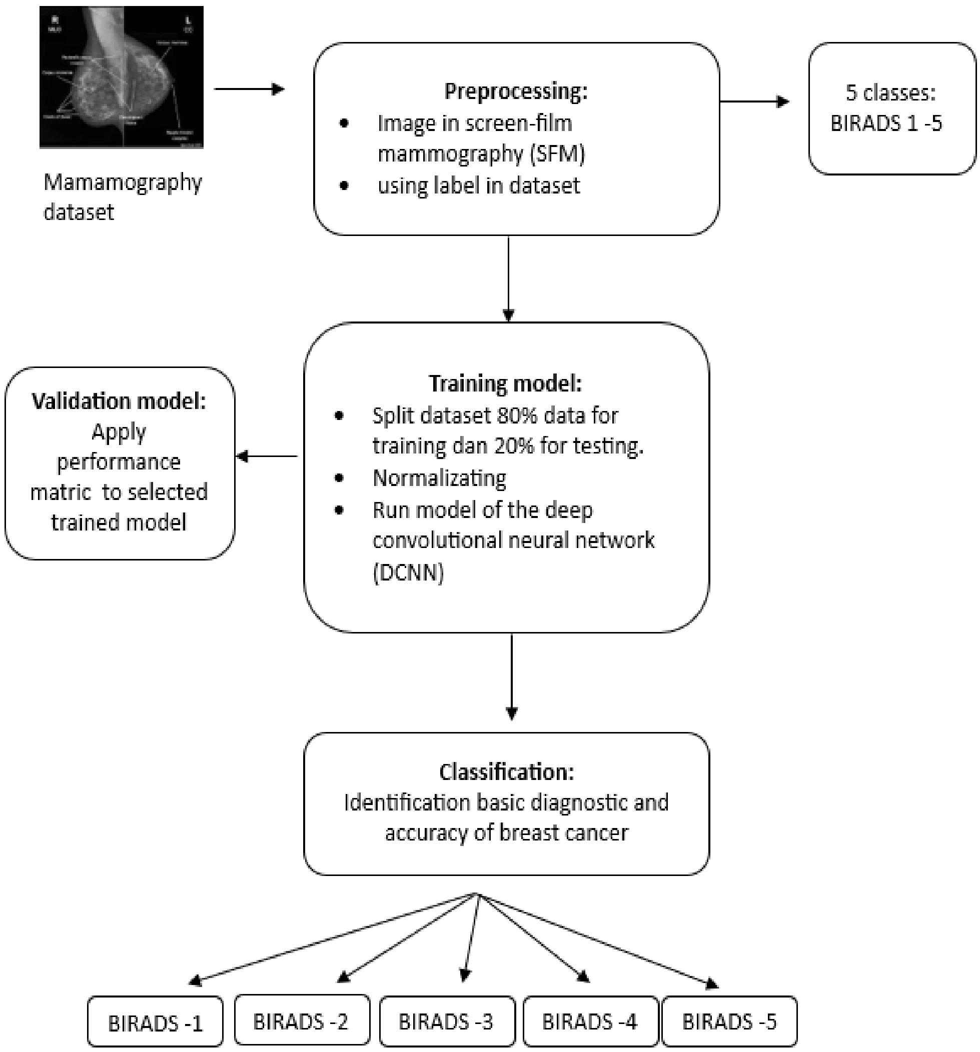


Figure 3. Research Process of AI Models

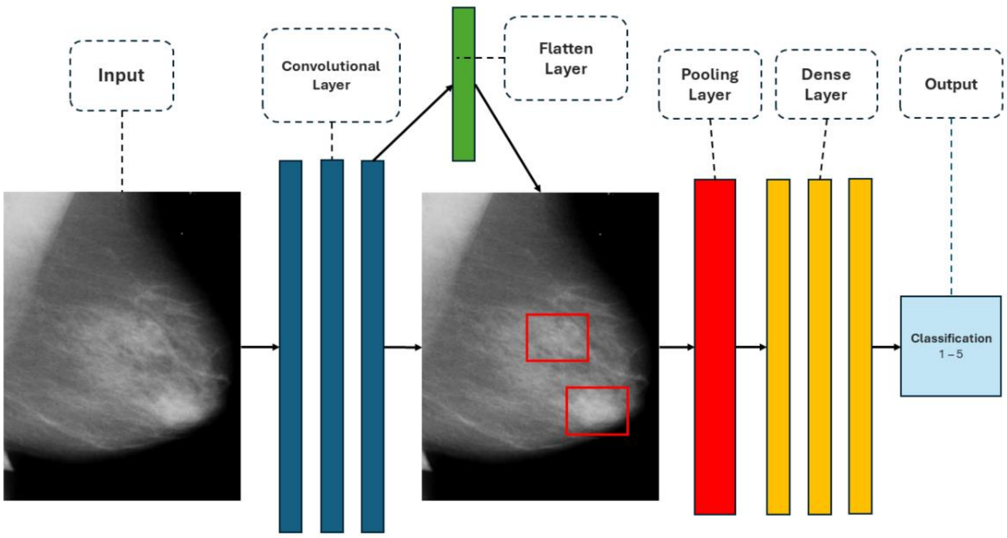


Figure 4. Conceptual Design of AI Model with a Convolutional Neural Network (CNN)

Table 2. The Configuration of CNN in the AI Models

Conv2D Layer	Filters: 32
	Kernel Size: (3, 3)
	Activation: ReLU
	Input Shape: (224, 224, 3)
MaxPooling2D Layer	Pool Size: (2, 2)
Flatten Layer	No additional parameters
Dense Layer	Units: 128
	Activation: ReLU
Output Layer	Units: Number of classes (determined by the length of the label encoder classes)
	Activation: Softmax
Optimizer	Adam
	Stochastic Gradient Descent (SGD)

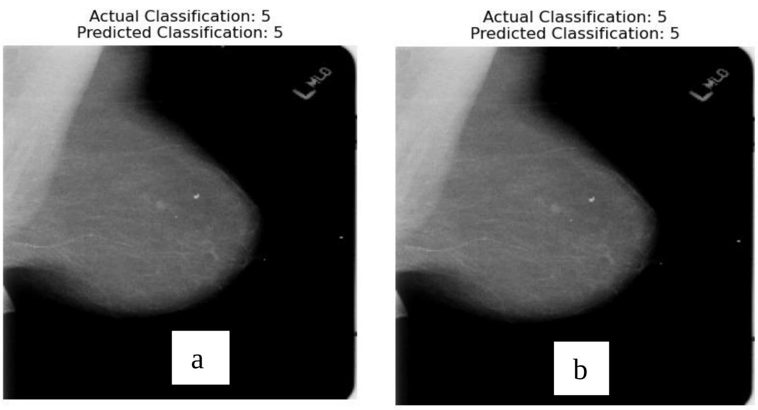
In this study, there are 6 (six) AI models using datasets with variations in model development, as described in table 3.

Table 3. Characteristics of 6 (six) AI Models

Model	**Optimizer**	**Parameter(s)**
I	Adam	1 image-type
II	Adam	2 image-types
III	Adam	3 image-types
IV	Stochastic Gradient Descent	1 image-type
V	Stochastic Gradient Descent	2 image-types
VI	Stochastic Gradient Descent	3 image-types

3. RESULT AND DISCUSSION

The AI models with CNN has been able to interpret images by classifying them in BIRADS categories 1-5. Some examples of images resulting from AI model interpretation are shown in figure 5:



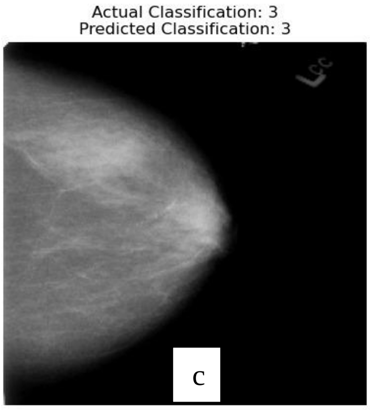


Figure 5. Image Interpretation Results by the AI Model with CNN (a,b,c)

The AI model assessment results in figure 5 show that image (a) shows inaccurate predictions, and in image (b c), the model prediction results are accurate.

The limitation of this research is that the data used is a database originating from kaggle.com. All data was used to develop the AI system without any changes or manipulations to improve image quality, while the available images have non-uniform resolution. The available dataset consists of two datasets: the training and testing datasets. The six AI models with CNN produced different levels of accuracy: model I (0.3528), model II (0.2975), model III (0.2658), model IV (0.3129), model V (0.3067), and model VI (0.3221). As shown in figure 6, the training accuracy of the AI models gradually increased with close to 1.0 accuracy. Whilst testing accuracy topped at around 0.3.

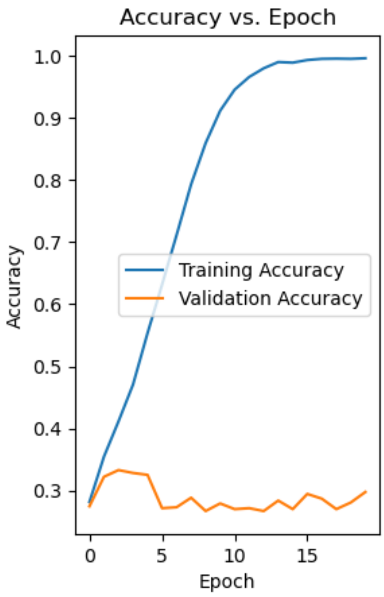


Figure 6. Training Accuracy vs Validation Accuracy

Image with good quality will increase the level of model accuracy. This process is generally done at the preprocessing stage. At the training stage, iteration is carried out to improve model accuracy [46] or with specific methods, for example, block-based image segmentation in the model input process [49].

4. CONCLUSION

Developing an AI model with CNN using the public dataset with a sample size of 1871 images provides prediction results with different accuracy rate of AI models. The accuracy of the AI models between 0.2658 - 0.3528.

5. SUGGESTIONS

Increasing the accuracy of the AI model can be done by improving the image quality before modeling, increasing the number of datasets, or carrying out a more profound iteration process so that the AI model with CNN can have a better level of accuracy.

REFERENCES

[1] H. Sung *et al.*, "Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries," *CA. Cancer J. Clin.*, vol. 71, no. 3, pp. 209–249, 2021, doi: 10.3322/caac.21660.

[2] J. Ferlay *et al.*, "Estimating the global cancer incidence and mortality in 2018: GLOBOCAN sources and methods," *Int. J. Cancer*, vol. 144, no. 8, pp. 1941–1953, 2019, doi: 10.1002/ijc.31937.

[3] S. C. B. Mandelbaltt J S, Stout N K, "Collaborative modelling of benefits and harms associated wirh different U.S. breast cancer screening strategies." .

[4] A. N. Giaquinto *et al.*, "Breast Cancer Statistics, 2022," *CA. Cancer J. Clin.*, vol. 72, no. 6, pp. 524–541, 2022, doi: 10.3322/caac.21754.

[5] WHO, "Cancer Screening and Early Detection," WHO, 2010. [Online]. Available: https://www.who.int/europe/news-room/fact-sheets/item/cancer-screening-and-early-detection-of-cancer.

[6] D. Surya Gowri and T. Amudha, "A review on mammogram image enhancement techniques for breast cancer detection," *Proc. - 2014 Int. Conf. Intell. Comput. Appl. ICICA 2014*, pp. 47–51, 2014, doi: 10.1109/ICICA.2014.19.

[7] I. dos S. S. V, Sinnicombe, SM Pinto Pereira, VA MCCormack, S Shiel, N Perry, "Full-field digital versus screen-film mammography: comparison within the UK breast screening program and systematic review of published data," *Radiology*, vol. 251, no. 2, pp. 347–358, 2009, [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK77894/.

[8] S. E. Singletary, "Rating the Risk Factors for Breast Cancer," *Ann. Surg.*, vol. 237, no. 4, pp. 474–482, 2003, doi: 10.1097/01.SLA.0000059969.64262.87.

[9] V. Bommel, "Interval cancers and bilateral cancers at breast cancer screening Interval Cancers and Bilateral Cancers at Breast Cancer Screening," no. 2020, 2023, doi: 10.26481/dis.20201203rb.

[10] M. J. M. Broeders, N. C. Onland-Moret, H. J. T. M. Rijken, J. H. C. L. Hendriks, A. L. M. Verbeek, and R. Holland, "Use of previous screening mammograms to identify features indicating cases that would have a possible gain in prognosis following earlier detection," *Eur. J. Cancer*, vol. 39, no. 12, pp. 1770–1775, 2003, doi: 10.1016/S0959-8049(03)00311-3.

[11] B. C. Y. R E Bird, T W Wallace, "Analysis of cancers missed at screening mammography," *Radiology*, vol. 184, no. 3, pp. 613–617, 1992, doi: https://doi.org/10.1148/radiology.184.3.1509041.

[12] A. S. Majid, E. S. De Paredes, R. D. Doherty, N. R. Sharma, and X. Salvador, "Missed Breast Carcinoma: Pitfalls and

Pearls," *Radiographics*, vol. 23, no. 4, pp. 881–895, 2003, doi: 10.1148/rg.234025083.

[13] R. D. Rosenberg *et al.*, "Performance benchmarks for screening mammography," *Radiology*, vol. 241, no. 1, pp. 55–66, 2006, doi: 10.1148/radiol.2411051504.

[14] Y. Bengio, Y. Lecun, and G. Hinton, "Deep learning for AI," *Commun. ACM*, vol. 64, no. 7, pp. 58–65, 2021, doi: 10.1145/3448250.

[15] Y. Lecun, M. ' Aurelio, and R. Google, "Deep learning tutorial," *Icml*, 2013, [Online]. Available: http://yann.lecun.comhttp//www.cs.toronto.edu/~ranzato.

[16] H. G. E. Krizhevsky A, Sutskever I, "ImageNet classification with deep convolutional neutral networks," *Neural Inf. Syst.*, vol. 25, no. 2, pp. 1–9, 2012, doi: 10.1201/9781420010749.

[17] T. C. & A. K. Krishnamurthy (Dj) Dvijotham, Jim Winkens, Melih Barsbey, Sumedh Ghaisas, Robert Stanforth, Nick Pawlowski, Patricia Strachan, Zahra Ahmed, Shekoofeh Azizi, Yoram Bachrach, Laura Culp, Mayank Daswani, Jan Freyberg, Christopher Kelly, Atilla Kiraly, Timo K, "Enhancing the reability and accuracy of AI-enabled diagnosis via complementary-driven deferral to clinicians," *Nat. Med.*, vol. 29, pp. 1814–1821, 2023, [Online]. Available: https://www.nature.com/articles/s41591-023-02437-x.

[18] K. Dembrower *et al.*, "Effect of artificial intelligence-based triaging of breast cancer screening mammograms on cancer detection and radiologist workload: a retrospective simulation study," *Lancet Digit. Heal.*, vol. 2, no. 9, pp. e468–e474, 2020, doi: 10.1016/S2589-7500(20)30185-0.

[19] A. Rodriguez-Ruiz *et al.*, "Stand-Alone Artificial Intelligence for Breast Cancer Detection in Mammography: Comparison With 101 Radiologists," *J. Natl. Cancer Inst.*, vol. 111, no. 9, pp. 916–922, 2019, doi: 10.1093/JNCI/DJY222.

[20] A. Rodríguez-Ruiz *et al.*, "Detection of breast cancer with mammography: Effect of an artificial intelligence support system," *Radiology*, vol. 290, no. 3, 2019, doi: 10.1148/radiol.2018181371.

[21] F. J. Gilbert *et al.*, "Single Reading with Computer-Aided Detection for Screening Mammography," *N. Engl. J. Med.*, vol. 359, no. 16, pp. 1675–1684, 2008, doi: 10.1056/nejmoa0803545.

[22] R. Hupse, *Detection of malignant masses in breast cancer screening by computer assisted decision making*. 2012.

[23] P. Wing and M. H. Langelier, "Workforce shortages in breast imaging: Impact on mammography utilization," *Am. J. Roentgenol.*, vol. 192, no. 2, pp. 370–378, 2009, doi: 10.2214/AJR.08.1665.

[24] A. Culpan, "Radiographer involvement in mammography image interpretation : a survey of United Kingdom practice .," *Radiography*, vol. 22, no. 4, pp. 306–312, 2016, doi: https://doi.org/10.1016/j.radi.2016.03.004.

[25] K. K. Evans, R. L. Birdwell, and J. M. Wolfe, "If You Don't Find It Often, You Often Don't Find It: Why Some Cancers Are Missed in Breast Cancer Screening," *PLoS One*, vol. 8, no. 5, pp. 1–6, 2013, doi: 10.1371/journal.pone.0064366.

[26] S. D. P T Huynh, AM Jarolimek, "The false-negative mammogram," *RadioGraphics*, vol. 18, no. 5, 1998, doi: htttps://doi.org/10.1148/radiographic.18.5.9747612.

[27] P. K. J. M. Health, K. Bowyer, D. Kopans, R. Moore, "The digital database for screening mammography," in *Digital Mammography*, 1998, [Online]. Available: https://link.springer.com/chapter/10.1007/978-94-011-5318-8_75.

[28] University of South Florida, "DDSM : Digital Database for Screening Mammography," *http://www.eng.usf.edu/*, 2012. http://www.eng.usf.edu/cvprg/mammography/database.html.

[29] Y. E. Almalki, T. A. Soomro, M. Irfan, S. K. Alduraibi, and A. Ali, "Impact of image enhancement module for analysis of mammogram images for diagnostics of breast cancer," *Sensors*, vol. 22, no. 1868, pp. 1–20, 2022, doi: 10.3390/healthcare10050801.

[30] A. Mračko, L. Vanovčanová, and I. Cimrák, "Mammography Datasets for Neural Networks—Survey," *J. Imaging*, vol. 9, no. 5, 2023, doi: 10.3390/jimaging9050095.

[31] Z. Jiao, X. Gao, Y. Wang, and J. Li, "A deep feature based framework for breast masses classification," *Neurocomputing*, vol. 197, pp. 221–231, 2016, doi: 10.1016/j.neucom.2016.02.060.

[32] C. Songsaeng, P. Woodtichartpreecha, and S. Chaichulee, "Multi-Scale Convolutional Neural Networks for Classification of Digital Mammograms with Breast Calcifications," *IEEE Access*, vol. 9, pp. 114741–114753, 2021, doi: 10.1109/ACCESS.2021.3104627.

[33] S. Gaur, V. Dialani, P. J. Slanetz, and R. L. Eisenberg, "Architectural distortion of the breast," *Am. J. Roentgenol.*, vol. 201, no. 5, pp. 662–670, 2013, doi: 10.2214/AJR.12.10153.

[34] Johnson B, "Asymmetries in mammography," *Radiol. Technol.*, vol. 92, pp. 281M-298M, 2021, [Online]. Available: http://www.radiologictechnology.org/content/92/3/281M.full.

[35] J. H. Youk, E. K. Kim, K. H. Ko, and M. J. Kim, "Asymmetric mammographic findings based on the fourth edition of BI-RADS: types, evaluation, and management.," *Radiographics*, vol. 29, no. 1, 2009, doi: 10.1148/rg.e33.

[36] D. A. Spak, J. S. Plaxco, L. Santiago, M. J. Dryden, and B. E. Dogan, "BI-RADS® fifth edition: A summary of changes," *Diagn. Interv. Imaging*, vol. 98, no. 3, pp. 179–190, 2017, doi: 10.1016/j.diii.2017.01.001.

[37] Y. Qiu *et al.*, "An initial investigation on developing a new method to predict short-term breast cancer risk based on deep learning technology," *Med. Imaging 2016 Comput. Diagnosis*, vol. 9785, p. 978521, 2016, doi: 10.1117/12.2216275.

[38] T. Fujioka *et al.*, "Distinction between benign and malignant breast masses at breast ultrasound using deep learning method with convolutional neural network," *Jpn. J. Radiol.*, no. 0123456789, 2019, doi: 10.1007/s11604-019-00831-5.

[39] D. Ribli, A. Horváth, Z. Unger, P. Pollner, and I. Csabai, "Detecting and classifying lesions in mammograms with Deep Learning," *Sci. Rep.*, vol. 8, no. 1, pp. 1–7, 2018, doi: 10.1038/s41598-018-22437-z.

[40] O. I. Ozsahin D U, Emegano D I, Uzun B, "The systematic review of artificial intelligence application in breast cancer diagnosis," *Diagnostics*, vol. 13, no. 45, pp. 2–18, 2022, doi: https://doi.org/10.3390/diagnostics13010045.

[41] B. J. Erickson, P. Korfiatis, Z. Akkus, and T. L. Kline, "Machine learning for medical imaging," *Radiographics*, vol. 37, no. 2, pp. 505–515, 2017, doi: 10.1148/rg.2017160130.

[42] K. Yasaka, H. Akai, A. Kunimatsu, S. Kiryu, and O. Abe, "Deep learning with convolutional neural network in radiology," *Jpn. J. Radiol.*, vol. 36, no. 4, pp. 257–272, 2018, doi: 10.1007/s11604-018-0726-3.

[43] P. Lakhani and B. Sundaram, "Deep learning at chest radiography: Automated classification of pulmonary tuberculosis by using convolutional neural networks," *Radiology*, vol. 284, no. 2, pp. 574–582, 2017, doi: 10.1148/radiol.2017162326.

[44] K. Yasaka, H. Akai, A. Kunimatsu, S. Kiryu, and O. Abe, "Deep learning with convolutional neural network in radiology," *Jpn. J. Radiol.*, vol. 36, no. 4, pp. 257–272, 2018, doi: 10.1007/s11604-018-0726-3.

[45] geeksforgeeks.org, "Introduction to convolutional neural network," *www.geeksforgeeks.org*, 2023. https://www.geeksforgeeks.org/introduction-convolution-neural-network/.

[46] K. Neshatpour, H. Homayoun, and A. Sasan, "ICNN: The iterative convolutional neural network," *ACM Trans. Embed.*

Comput. Syst., vol. 18, no. 6, 2019, doi: 10.1145/3355553.

[47] D. A. Anam, L. Novamizanti, and S. Rizal, "KLASIFIKASI PATOLOGI MAKULA PADA RETINA BERDASARKAN CITRA RETINAL OCT MENGGUNAKAN CONVOLUTIONAL NEURAL NETWORK (Classifying Retinal Pathology Using OCT Retinal Imaging With Convolutional Neural Network)," *e-Proceeding Eng.*, vol. 8, no. 5, pp. 5072–5082, 2021, [Online]. Available: https://www.kaggle.com/paultimothymooney/kermany2018.

[48] D. S. Candra, "Implementasi Convolutional Neural Network (CNN) Untuk Klasifikasi Citra Bunga," vol. 16, no. 1, pp. 2580–2582, 2020.

[49] K. J. Tsai *et al.*, "A High-Performance Deep Neural Network Model for BI-RADS Classification of Screening Mammography," *Sensors*, vol. 22, no. 3, 2022, doi: 10.3390/s22031160.