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Cervical Cancer Diagnosis System using Convolutional Neural Network ResidualNet

DIAN C. RINI NOVITASARI, PUTRI WULANDARI, DINA ZATUSIVA HAQ
UIN Sunan Ampel Surabaya, Jl. Ahmad Yani 117, Surabaya, 60237, Indonesia, (e-mail: diancrini@uinsby.ac.id, h72216063@gmail.com)

Corresponding author: Dian C. Rini Novitasari (e-mail: diancrini@uinsby.ac.id).

ABSTRACT Cervical cancer is a deadly disease attacking women. It represents 6.6% of all female cancers. The stadium of cervical cancer is determined based on the presence of carcinoma. The cervical cancer classification system can be used to help medical workers to analyze the stadium of cervical cancer. In this study, cervical cancer stages were divided into five classes, namely, normal cervix, stadium I, stadium II, stadium III, and stadium IV based on colposcopy images. The proposed method is one of deep learning methods, that is convolutional neural network (CNN) using deep residual network (ResidualNet) architecture. This study compared ResidualNet-18, ResidualNet-50, and ResidualNet-101 models and some conventional methods. The comparison results show that ResidualNet is more accurate than conventional methods. From the experiment, based on the accuracy value and elapsed time, ResidualNet-50 is worth using for cervical cancer classification. The result of this evaluation is higher than the maximum achievement of the ResidualNet-18 architecture. In addition, the elapsed time of the classification process using the ResidualNet-50 architecture with the accuracy, sensitivity, and specificity values reaching 100% is shorter than ResidualNet-101, which is 4397 s.

KEYWORDS cervical cancer; colposcopy; computer aided diagnosis system; deep learning; deep residual network.

I. INTRODUCTION

CERVICAL cancer is the fourth highest cause of the women's death in the world [1]. Cervical cancer is caused by several factors, such as environmental and gene factors [2]. It is generally caused by Human Papilloma Virus (HPV) [3, 4]. It is transmitted through sexual intercourse [5]. In the early stadium of cancer, the disease does not have specific symptoms. However, in the severe stadium, the pain spreads to the feet [6] and even to distant organs such as the lungs, liver, bones, etc. [7]. Early diagnosis can determine a proper treatment to prevent death and reduce the mortality rate of the disease [8]. There are various cervical cancer tests, such as colposcopy test which is one of the main diagnostic methods in the U.S. used to diagnose the cancer [9]. It is performed by taking an image on the genital areas (cervix, vulva and vagina) that focus on the metaplastic epithelium using a colposcope [9, 10]. The surface of epithelium squamous of the normal cervix is pink and smooth. If it appears uneven, acetowhite, punctate and mosaic, it can be identified as the presence of cancer [11].

Nowadays, the diagnosis of disease using artificial intelligence (AI) has been widely used by medical workers to help them in the diagnosis of various types of cancer, including cervical cancer. One of the products of artificial intelligence technology is Computer-Aided Diagnosis (CAD) system. CAD system has an important role as it performs medical image processing to diagnose the disease with less possibility of error diagnostic and reduce the time of diagnosis [10]. Previous study used CAD system to identify or detect some disease. In [12–15], several image processing methods were developed to identify cervical cancer automatically. In [16], convolutional neural networks (CNN) were applied to the colposcopy image dataset and it is classified into normal and cancer classes.

CNN has been widely used by researchers to analyze an object as it is claimed as the best model in solving object recognition problems [17]. In [18] and [19] it was shown that CNN is one method in deep learning that is able to detect cancer with good performance and successfully classify natural and biomedical images. In [20, 21], the average of accuracy value of cancer classification cases shows the values above 90%. There are various CNN architectures proposed by many researchers, for example, LeNet, AlexNet, ZFNet, GoogleNet, VGGNet, and ResidualNet [22]. In the ResidualNet (Deep Residual Network) architecture, the ImageNet dataset is classified properly and obtains the accuracy values of 80.62% for Top-1 [23] and 3.57% for Top-5 [22]. Jiang, et al. classified the histopathological image of breast cancer using CNN with the SE-ResidualNet architecture and obtained the accuracy value between 98.87% to 99.34% for binary classification and 90.66% to 93.81% for multiclass classification [19]. Ismael, et al. obtained the accuracy of 99% for brain MRI image classification into three brain tumor classes using Residual Network [24]. Chen, et al. introduced the fine-tuning residual network (ResidualNet) algorithm for automatic mammography classification and obtained the value of accuracy, sensitivity, specificity, and AUC, corresponding to 93.15%, 93.83%, 92.17%, and 0.95 [25]. ResidualNet allows in-depth Neural Network training by reducing the computational time and the complexity compared with other architectures [22]. The strength of ResidualNet model compared with other CNN architecture models is that the performance of the model does not decrease even though the architecture is getting deeper. ResidualNet has several types of architecture based on the number of convolution layers used, starting from 18, 34, 50, 101, and up to 152 layers [23, 26].

Based on the previous studies, the proposed method of the study is deep residual network (ResidualNet) architecture to classify cervical cancer stadium based on colposcopy images. In this study the ResidualNet-18, ResidualNet-50, and ResidualNet-101 models were trained. Colposcopy data were classified into five classes, namely, normal cervix, stadium I, stadium II, stadium III, and stadium IV. The results of this research can be used to help medical workers to analyze the stadium of patients' cervical cancer to determine the proper treatment for the patients, so it can minimize the mortality rate of women with cervical cancer.

II. LITERATURE REVIEW

A. DATA AUGMENTATION

Data augmentation is a technique to increase image variance for training datasets to build better learning models based on the initial dataset. Data augmentation algorithm of image is diverse, namely, geometric transformation, color modification, kernel filter, GAN, random cropping, etc. [27]. In most cases, the method applied for data augmentation is geometric transformation [28], it is related to the position of the pixels in image, such as rotation, reflection, dilatation, translation, shear, and transformation affine.

In this study, the data augmentation methods used are rotation, reflection, and dilatation. The rotation transformation applied to the images is random rotating with an angle between 0º to 360º. For reflection transformation, the transformation applied to the image is random mirroring of the x-axis, y-axis and (x,y)-axis. Then, at the dilatation transformation, scaling is applied to the image randomly at a scale of 0.5 to 2.

B. DEEP RESIDUAL NETWORK

Deep Residual Network (ResidualNet) is one of CNN architectures proposed by He et al. The architecture was built to solve the problems on the Deep Learning training as it generally takes quite a lot of time and limits a certain number of layers. The solution to the problem proposed by ResidualNet is to apply skip connection or shortcut [23].

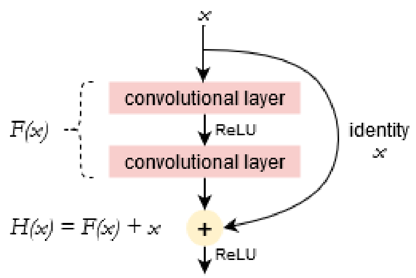

Figure 1. Deep Residual Network Block

He et al. adopted residual learning to be applied to several layers of convolution layers. Among the stack of convolution layers, there are residual blocks, where these residual blocks are the addition of the initial convolution layer $H(x)$ results to the convolution layer after two or three times the of convolutional process $F(x)$, under the condition that the output size of initial convolution layer has the same size as the output of the convolution layer afterwards. Accordingly, the residual block in this case is when learning $F(x)$ is the residual of $H(x)$- x by assuming x is an identity function.

$$F(x) = H(x) - x. \quad (1)$$

$$H(x) = F(x) + x. \quad (2)$$

ResidualNet has several types of architecture based on the number of convolution layers used [29]. The two initial layers of the ResidualNet architecture resemble GoogleNet by performing a 7×7 convolution and 3×3 max pooling with the strides' number of 2 [30]. In ResidualNet-18, each residual block consists of 2 convolution layers, while the size of the filter in the convolution layer is always 3×3 with different depths. Whereas in ResidualNet-50 and ResidualNet-101, each residual block consists of 3 convolution layers. The details of ResidualNet-18, ResidualNet-50 and ResidualNet-101 architectures are shown in Fig. 2.

Layer Name	Output Size	ResidualNet-18	ResidualNet-50	ResidualNet-101
	224 x 224 x 3	image		
Conv1	112 x 112	7 x 7 conv, 64, /2		
		3 x 3 maxpool, /2		
Conv2_x	56 x 56	[3 x 3 conv, 64; 3 x 3 conv, 64] x 2	[1 x 1 conv, 64; 3 x 3 conv, 64; 1 x 1 conv, 256] x 3	[1 x 1 conv, 64; 3 x 3 conv, 64; 1 x 1 conv, 256] x 3
Conv3_x	28 x 28	[3 x 3 conv, 128; 3 x 3 conv, 128] x 2	[1 x 1 conv, 128; 3 x 3 conv, 128; 1 x 1 conv, 512] x 4	[1 x 1 conv, 128; 3 x 3 conv, 128; 1 x 1 conv, 512] x 4
Conv4_x	14 x 14	[3 x 3 conv, 256; 3 x 3 conv, 256] x 2	[1 x 1 conv, 256; 3 x 3 conv, 256; 1 x 1 conv, 1024] x 6	[1 x 1 conv, 256; 3 x 3 conv, 256; 1 x 1 conv, 1024] x 23
Conv5_x	7 x 7	[3 x 3 conv, 512; 3 x 3 conv, 512] x 2	[1 x 1 conv, 512; 3 x 3 conv, 512; 1 x 1 conv, 2048] x 3	[1 x 1 conv, 512; 3 x 3 conv, 512; 1 x 1 conv, 2048] x 3
Classification Layer	5	7 x 7 avg pool, /7		
		2048 x 5 fc		
		softmax		

Figure 2. ResidualNet-18, ResidualNet-50 and ResidualNet-101 architectures for 5 classes

C. PERFORMANCE EVALUATION

Performance evaluation in a classification system is important to know how the system works to classify data. In measuring the performance of classification systems, confusion matrix is used to compare the results of classification by the system with the actual classification results [22, 31].

Table 1. Confusion Matrix

Predict	Actual			
	Class 1	Class 2	Class 3	Class 4
Class 1	TN	FP	TN	TN
Class 2	FN	TP	FN	FN
Class 3	TN	FP	TN	TN
Class 4	TN	FP	TN	TN

In confusion matrix, there are terms, namely, true positive (TP), false positive (FP), false negative (FN), and true negative (TN) [22]. Evaluation of the classification system (accuracy, specificity, and sensitivity) based on the values of TP, FP, FN, and TN using Eq 3-5, where n is the number of classes.

$$\text{Accuracy} = \frac{\frac{TP+TN}{TP+FN+FP+TN}}{n} \quad (3)$$

$$\text{Specificity} = \frac{\frac{TN}{TN+FP}}{n}. \quad (4)$$

$$\text{TPR/ Sensitivity} = \frac{\frac{TP}{TP+FN}}{n}. \quad (5)$$

III. THE METHODOLOGY

In this study, the data used were colposcopy image data obtained from Geneva Foundation (https://www.gfmer.ch/). The data consisted of five stadium of cervical cancer, namely, normal cervix, stadium I, stadium II, stadium III, and stadium IV.

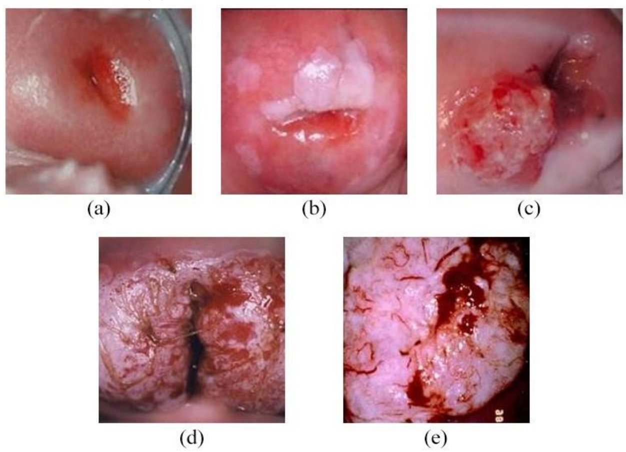

Figure 3. Colposcopy Images: (a) Normal Cervix, (b) Stadium I, (c) Stadium II, (d) Stadium III, (e) Stadium IV

The proposed methods of this study were pre-processing stage, training the classification model, and testing the model of cervical cancer classification system. The first step of the pre-processing stage was applied to the cropping process because the images of the dataset had different sizes. Then, data augmentation was applied to the system to increase the number of datasets as the more data trained in deep learning, the better the system at recognizing images. Following the data augmentation step, the data were divided into training data and testing data for training and testing classification model with the ratio of 80:20. Furthermore, training the classification model was conducted using the ResidualNet-18, ResidualNet-50 and ResidualNet-101 architecture model training to obtain the optimal model, then the model was used to classify testing data for evaluation of the cervical cancer classification system.

IV. RESULT AND DISCUSSION

In this study, three architectural models of ResidualNet were proposed to classify cervical cancer stadium based on colposcopy images. Each model went through the same steps. The first step of purposed method was pre-processing stage. The images in dataset had different sizes, accordingly, cropping process was applied to obtain the focus on cervix area. Determining the size of the image was based on [24], while the size of input image on ResidualNet architecture was 224×224. Following the cropping process, data augmentation was applied to increase the number of training data. The various training data enabled to increase the model's learning ability to recognize image patterns. The data augmentations used were rotation, reflection, and dilatation. The results of geometry transformation are shown in Fig. 4.

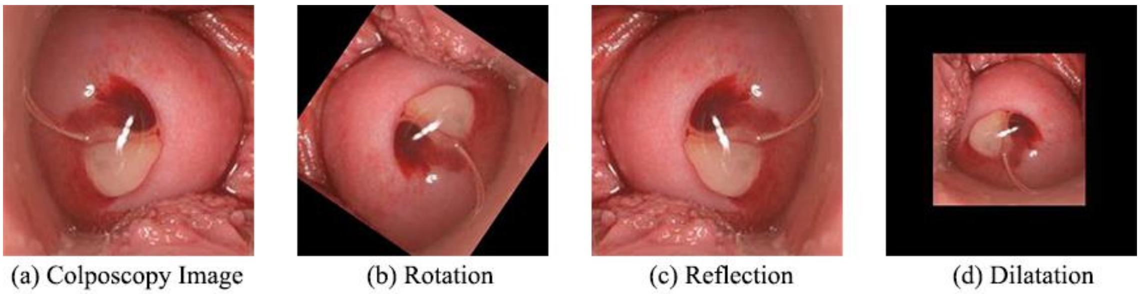

Figure 4. Sample of Geometry Transformation Results for Data Augmentation

Based on data augmentation process, it was obtained 2000 colposcopy image data. Furthermore, the data were divided into training data and testing data with the ratio of 80:20. Accordingly, the number of the training data was 1600 data and that of the testing data was 400 data, in which there were 80 data for each cervical cancer class. Each datum was applied to three architectural models of ResidualNet (ResidualNet-18, ResidualNet-50 and ResidualNet-101). Each architecture trained training data to build a cervical cancer classification model, so an optimal model was obtained to classify test data. The results of the classification model were compared with the actual data using confusion matrix to obtain accuracy, sensitivity, and specificity. The comparison of conventional feature extraction and classification methods with the CNN ResidualNet model is shown in Table 2.

Table 2. Model Performance Evaluation Results

Method		Akurasi (%)	Sensitifitas (%)	Spesifisitas (%)	Elapsed Time (s)
GLCM+Backpropagation		71.49	78.75	72.58	2.08
GLRLM+ Backpropagation		**96.26**	**96.78**	**96.40**	**6.52**
HOG+ Backpropagation		82.71	82.73	80.89	7.82
GLCM+ELM		94.86	96.46	94.64	1.09
GLRLM+ ELM		**95.79**	**96.73**	**95.85**	**4.10**
HOG+ ELM		85.05	87.47	82.98	5.08
ResidualNet18	**Batchsize 4**	99.07	98.93	99.13	2489
	Batchsize 8	99.53	99.57	99.57	1970
	Batchsize 16	**99.53**	**99.46**	**99.23**	**1490**
ResidualNet50	**Batchsize 4**	99.07	99.03	99.13	6405
	Batchsize 8	100	100	100	4831
	Batchsize 16	**100**	**100**	**100**	**4397**
ResidualNet101	**Batchsize 4**	97.20	98.18	97.06	11946
	Batchsize 8	99.53	99.67	99.57	8789
	Batchsize 16	**100**	**100**	**100**	**8653**

Based on Table 2, it can be seen that ResidualNet has better performance than conventional methods. The highest accuracy in the conventional method is obtained by combining the Gray Level Run Length Matrix (GLRLM) and backpropagation methods, which is 96.26%. Judging from the average accuracy of the Extreme Learning Machine (ELM) classification method is superior to the backpropagation method, and the GLRLM feature extraction method has a better performance in representing cervical cancer images. However, when compared to the CNN ResidualNet method, the conventional classification method produces a model with a lower level of accuracy.

The accuracy value of the CNN ResidualNet method reaches 100% with a batch size of 16 on ResidualNet-50 and ResidualNet-101. Based on the average accuracy value, the ResidualNet-50 architecture can recognize cervical cancer image patterns well. The ResidualNet-50 architecture achieves 100% accuracy on batch sizes 8 and 16 with a relatively short time of fewer than 2 hours. The graph of training progress on ResidualNet-50 batchsize 16 is shown in Figure 5. The graph of the comparison of accuracy with batchsize trials on each ResidualNet architecture is shown in Figure 5.

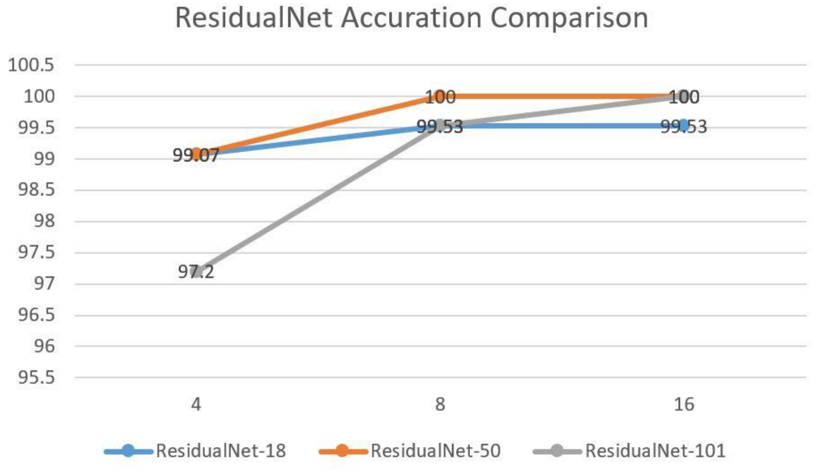

Figure 5. ResidualNet Accuration Comparison

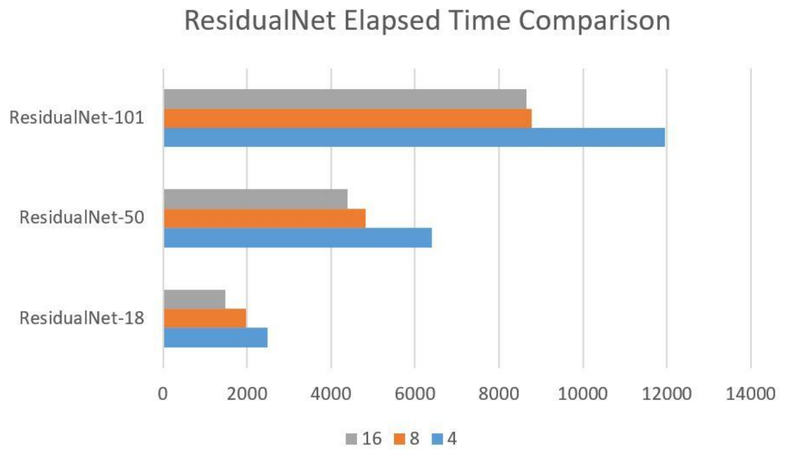

Figure 6. ResidualNet Elapsed Time Comparison

Based on Figure 5 it is shown that more batchsize can produce higher accuracy values. This condition happens because the use of high batchsize allows the model to learn more data. However, using too large batch size in the CNN method requires higher computer specifications. The larger the batchsize value, the shorter the time required, as shown in the graph in Figure 6.

Based on Figure 5 and Figure 6, in this study it is shown that the use of the ResidualNet-50 architecture is quite optimal, in terms of accuracy reaching 100% and in a relatively short time compared to the achievement of 100% accuracy by the ResidualNet-101 architecture. The architecture of ResidualNet-50 batchsize 16 can achieve maximum accuracy of 100% with a training time of 4397 s. In ResidualNet-18 architecture, the average duration of training time is shorter than other ResidualNet architectures, namely 1983 s, but the maximum accuracy obtained is only 99.53%. The training progress of the ResidualNet-50 architecture classification with a batch size of 16 is shown in Figure 7. It can be seen that the accuracy value is increasing with each iteration and is stable at 100% accuracy value in the range of 5 iterations.

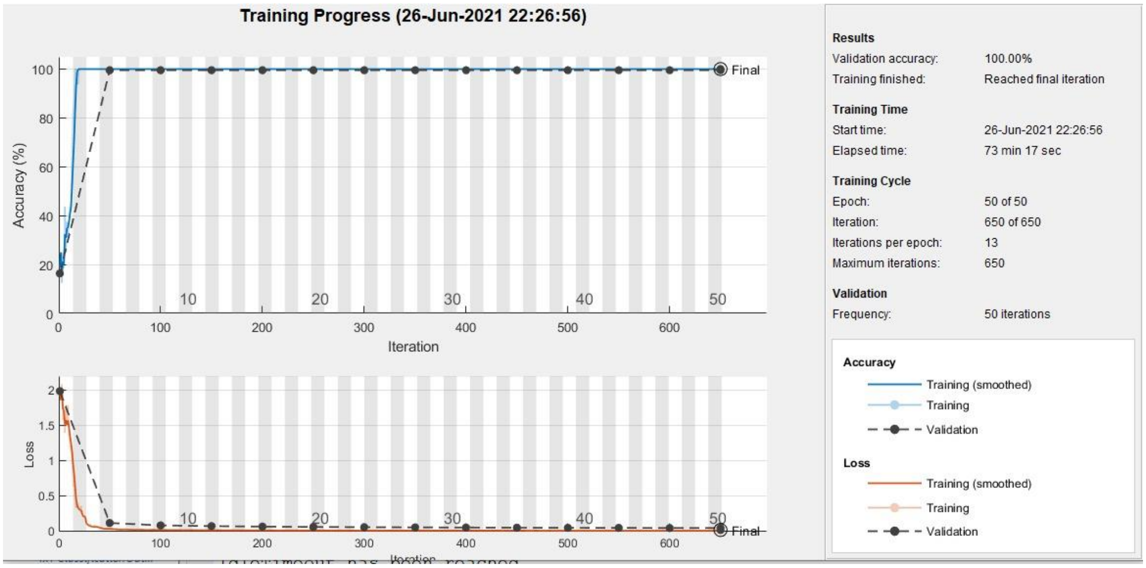

Figure 7. ResidualNet Training Progress

Data dramatically affects the performance of the ResidualNet architecture. In different datasets, the comparison of the accuracy values of each architecture will also be different. A sample of the ResidualNet architecture feature map generated from the feature learning process of image data is shown in Figure 8. This feature learning process produces 2048 features as input data in the classification layer.

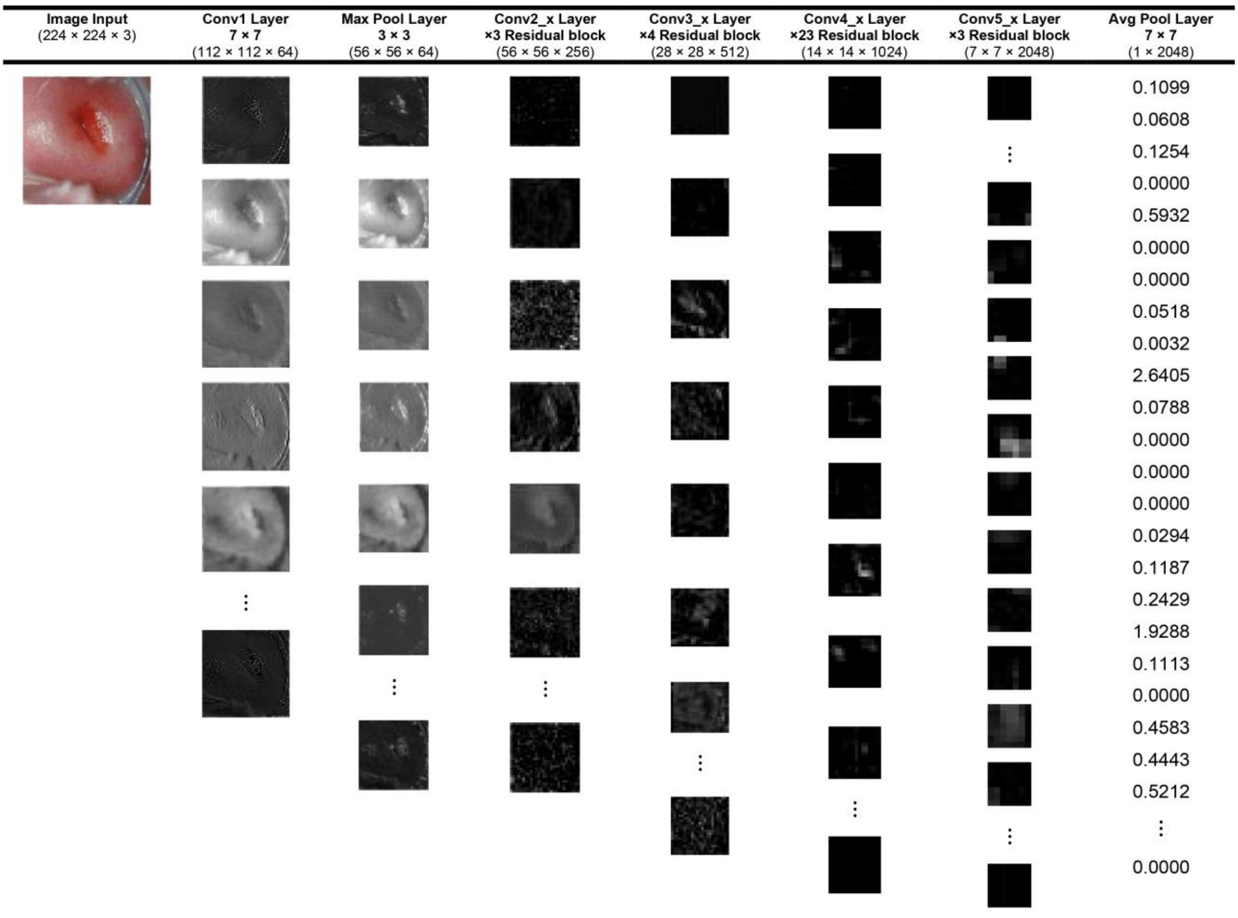

Figure 8. Sample of Feature Learning Layer Process in ResidualNet-101 model

ResidualNet architecture has a high layer depth, and each layer has a weight, so there are many parameters and a long computation time is required. An architectural development was carried out to overcome the weaknesses in the ResidualNet architecture, namely the Dense Convolutional Network (DenseNet) architecture. DenseNet can overcome the problem of vanishing-gradient descent and substantially reduce the number of parameters. In future research, DenseNet architecture can be used, and it is hoped that it can accelerate the computational process and result in high accuracy [32, 33]. In addition, accelerating the computational process and increasing accuracy results can also be done using the Dilated Convolutional Neural Network method, wherein research [34] the Dilated CNN method can reduce training time by 12.99% and increase accuracy by 2.86%.

V. CONCLUSION

Based on the results of the study, the model of classification system for cervical cancer trained was a good classification model and the best learning model obtained from architecture with the greatest number of layers was ResidualNet model.

The CNN ResidualNet method was carried out several trials, such as testing the ResidualNet architecture (ResidualNet-18, ResidualNet-50, and ResidualNet-101) and testing batchsize (4, 8, and 16). Based on several trials conducted, it can be seen that the more layers the ResidualNet architecture have, the more computational time it takes. In the classification process, batchsize correlates with training time and accuracy results. The bigger the batch size is, the greater the accuracy and the shorter the duration of the training. The most optimal ResidualNet architecture in the implementation of cervical cancer detection is ResidualNet -50 with an accuracy reaching 100% and a relatively short time, 4397 s.

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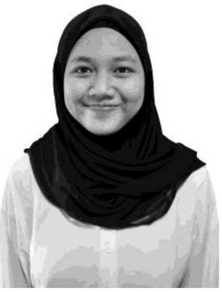
DIAN C. RINI NOVITASARI, a researcher at Department of Mathematic, UIN Sunan Ampel Surabaya. Department of Informatics Institut Teknologi Sepuluh Nopember Surabaya. In 2018 she starts Ph.D. in Department Mathematics and Sciences Airlangga University. Her research interests include mathematical computation, pattern recognition, machine learning, data science, and applications of artificial intelligence.



Putri Wulandari, graduated from Mathematic Department, UIN Sunan Ampel Surabaya. Her main areas of research interest include mathematical computation, machine learning, artificial intelligence, and deep learning.

DINA ZATUSIVA HAQ, graduated from Mathematic Department, UIN Sunan Ampel Surabaya. Her main areas of research interest include data mining, mathematical computation, machine learning, artificial intelligence, and deep learning.