Classification of Cervical Precancerous Cell of ThinPrep Images Based on Deep Learning Model AlexNet and InceptionV3

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Abstract:
Cervical cancer is one of the deadliest diseases in the world, responsible for the greatest number of fatalities. Around 569.847 new cervical cancer cases are recorded every year. Efforts to prevent this condition can be conducted by early identification. There are several methods to detect cervical cancer, one of which is ThinPrep. In identifying cervical cancer, a neural network can be utilized as an alternative. AlexNet and InceptionV3 are neural network frequently applied to detect various diseases. In this study cervical cell images were classified based on cell severity, using deep learning models AlexNet and InceptionV3. The results it can be known that Inception V3 has a better performance based on the performance matrix analysis of the both models. The best performance matrix results for InceptionV3 are 89.80% for accuracy, 89.81% for precision, 91.17% for sensitivity, 94.49% for specificity, and 89.26% for F-score. However, AlexNet's training time have much faster than InceptionV3, with an average training time 57 seconds and fastest training time 55 seconds.

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I. Introduction

Cervical cancer is one of the leading causes of mortality for women throughout the world[1][2]. Approximately 569,847 new cases

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***Abstract*—Cervical cancer is one of the deadliest diseases in the world, responsible for the greatest number of fatalities. Around 569,847 new cervical cancer cases are recorded every year. Efforts to prevent this condition can be conducted by early identification. There are several methods to detect cervical cancer, one of which is ThinPrep. In identifying cervical cancer, a neural network can be utilized as an alternative. AlexNet and InceptionV3 are neural network frequently applied to detect various diseases. In this study cervical cell images were classified based on cell severity, using deep learning models AlexNet and InceptionV3. The results it can be known that Inception V3 has a better performance based on the performance matrix analysis of the both models. The best performance matrix results for InceptionV3 are 89,80% for accuracy, 89,81% for precision, 91,17% for sensitivity, 94,49% for specificity, and 89,26% for F-score. However, AlexNet's training time have much faster than InceptionV3, with an average training time 57 seconds and fastest training time 55 seconds.**

Keywords—Cervical Cell, Cervical Cancer, Deep Learning, AlexNet, GoogleNet, Inceptionv3

I. INTRODUCTION

Cervical cancer is one of the leading causes of mortality for women throughout the world[1][2]. Approximately 569,847 new cases of cervical cancer are diagnosed each year, making it the second deadliest cancer [3]. It is estimated that 90% of cervical cancers develop in low- and middle-income countries. The absence of an early screening program for cervical cancer [1] [4] is to blame for this. Hence, to prevent this condition from worsening, it is necessary to perform an early screening for the disease to provide further treatment [3]. In developed countries, cervical cancer prevention has been accomplished using a variety of ways.

Numerous methods have been employed for the early detection of cervical cancer, one of which is ThinPrep. It is liquid-based cytology (LBC) cervical cancer detection method, which is a development of the conventional Pap Smear method [5] [6]. To obtain the diagnosis results, the analysis is carried out manually by a pathologist. Unfortunately, this method is quite time-consuming due to the restricted number of pathologists. Moreover, the outcomes of a manual analysis are more likely to be objective.

With advances in science, computers can assist in diagnosing. Thus, artificial intelligence algorithms can be implemented to classify disease types based on digital images. The neural network method is an alternative in computer-based cancer diagnosis, one of which is the Convolutional Neural Network (CNN) [5]. CNN is a fairly popular method in cervical cell classification, as research in 2014 Cervical Cytoplasm and Nuclei images yielded an accuracy of 94.50% [7]. In the following year, Hussain et al. conducted research by focusing on segmentation by changing the value of the convolutional layer, resulting in a Zijdenbos similarity index value of 97% and an accuracy of 98.8% [8][9].

Several studies classified cervical cells using the AlexNet model [10],[11], [12], and [13]. Kurnianingsih et al. applied four deep learning methods to identify cervical cancer cells in their study, encompassing AlexNet, GoogleNet, ResNet, and DenseNet, with GoogleNet achieving the highest accuracy of 94.5% [10]. In 2021 Swarm Intelligence has been used optimize the AlexNet method to classify cervical cancer cells. The research obtained an accuracy of 67%, with 6.22% higher than the standard value [11]. T, Haryanto et al. in 2020 using AlexNet as CNN algorithm to identification Cervical cancer through pap-smear images. The results show that using the utilization padding scheme on the AlexNet architecture can increase the accuracy of the model slightly significantly from 84.88% to 87.32% [12]. Three CNN models (i.e. AlexNet, Inception-V3 and ResNet50-V2) have been used to classify the cervical image to diagnose cervical cancer. The result obtained, ResNet50-V2 performed the best [13].

In addition to cervical cancer, AlexNet was also utilized in other image detection, such as that conducted by S. Lu, Z. Lu, and YD Zhang, by combining the AlexNet method and transfer learning as a method for classifying brain cell images, and produced 100% accuracy[14].

Another CNN's model used for cervical cell classification is InceptionV3. There are several studies using InceptionV3 to classify the cervical image [15], [16], [17], and [18]. In 2020 Dong, et.al applied Inception v3 and combine with artificial extracted features to classify cervical cell images. The accuracy of more than 98% is achieved [15]. Khamparia et al in their study using CNN models (i.e. InceptionV3, VGG19, SqueezeNet and ResNet50) to classify cervical cancer in Pap smear images. The results ResNet50 achieved the higher classification rate of 97.89% [16]. Li, C et al applied Inception-V3 to classify cervical histopathology image, with the average accuracy of they achieved 77.3% [17].

In additional of classification using InceptionV3 in another image detection conducted by Qing Guan et al, in their study diagnosis of lymph node in cytological images. The results of this study achieve total accuracy on the test dataset was 89.62%.[18]

Based on the problem and several literature study the purpose of this study is to construct a classification algorithm based on deep learning utilizing the pre-trained AlexNet model and InceptionV3, considering the background and past research. This work is structured with subsection one serving as the introduction, subsection two presenting the research method, subsection three describing the research findings, and the last subsection displaying the conclusion.

II. Methods

A. Data Collection

The 283 cervical cell images analyzed in this research were classified as High-grade Squamous Intraepithelial Lesion (HSIL), Low-grade Squamous Intraepithelial Lesion (LSIL), and Normal. The image data were obtained from the Universiti Sains Malaysia Hospital. The image data have been verified and adhered to the Universiti Sains Malaysia's code of ethics.

B. System Design

The process of classification of cervical cell image is carried out with several steps. This system has three main steps, first one is Pre-processing, Training, and Testing. The system design in this research illustrated in Figure 1. MATLAB version R2020a was utilized as a software to process the system design cervical images. Table 1 displays the computer hardware specification for processing cervical cells.

TABLE I. HARDWARE SPECIFICATION

Processor	Intel® Core i5 9400f
RAM Memory	16GB
GPU	Nividia RTX 2060 6GB

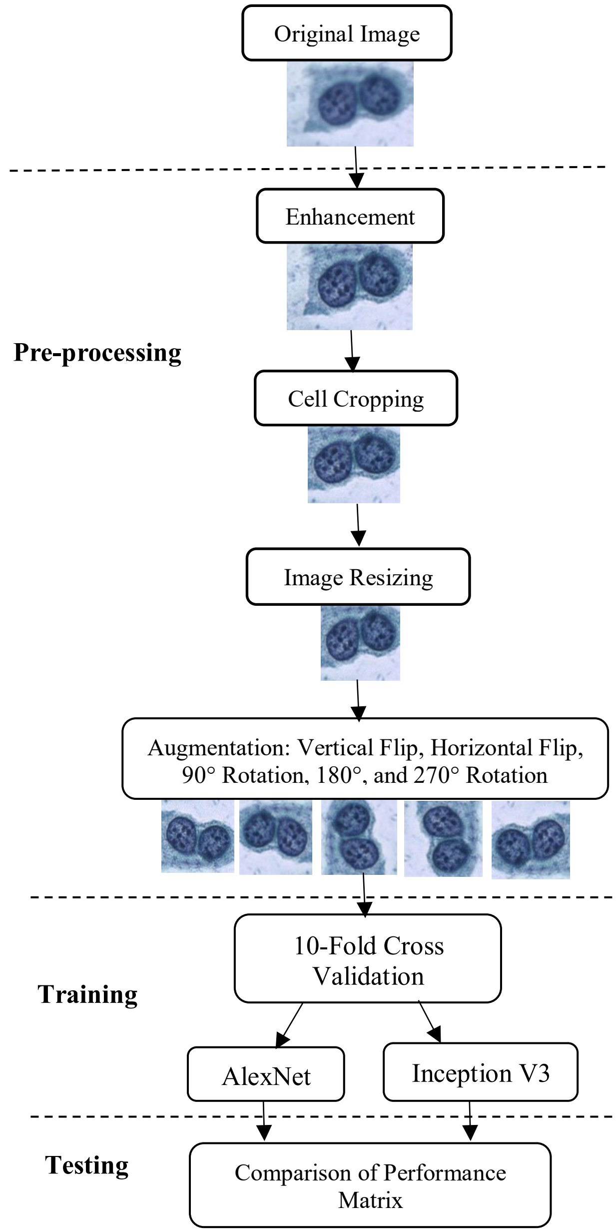


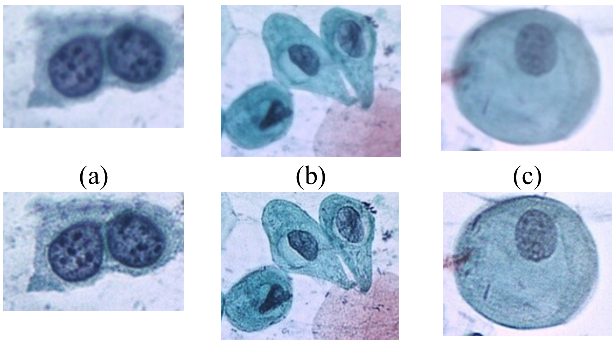
Fig. 1. Flowchart of the system design

C. Pre-processing

Pre-processing is the stage to prepare image data to be used appropriately in the training and testing processes. Before performing pre-processing, the cervical cell data were arranged first by classifying the images into three classes: HSIL (class 1), LSIL (class 2), and Normal (class 3), and dividing the number of images for each class equally, namely 60 images.

Each class was broken into training and testing folders. Training accounted for 90%, whereas testing accounted for 10% of the overall images. All the images from the three classes were combined into one folder in the data set testing. After the two data sets were ready, pre-processing began. Figure 1 demonstrates the entire flow and examples of the process.

1) Image Enhancment: The use of an enhancing method proved beneficial as a means of image improvement. For improved clarity, the original cervical images were sharpened. The result of the enhancement shown in Figure 2.



(a) (b) (c)

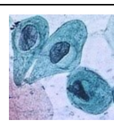
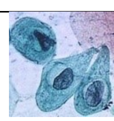
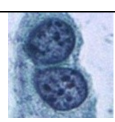
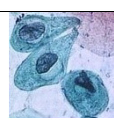
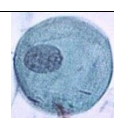
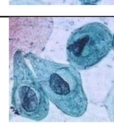
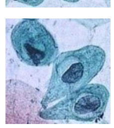
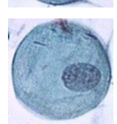
(d) (e) (f)

Fig. 2. Result of image before and after hancement ***(a,b,c** Original Images* ***d,e,f**, Images after enhancement)*

2) Cell Cropping: Because the shape and size of the cervical cell images were varied, cropping the image was carried out to obtain a consistent image size. Cropping was accomplished by concentrating on the cervical cell nucleus images.

3) Image Resizing: At this stage, the image size was adjusted to match the model algorithm used, in this case, AlexNet, with a required image size of 227x227 pixels and 299x299 pixels for InceptionV3.

TABLE II. AUGMENTATION RESULT

	Class 1	**Class 2**	**Class3**
Vertical Flip			
Horizontal Flip			
90° Rotation			
180° Rotation			
270° Rotation			

4) Image Augmentation: Image augmentation refers to reproducing images using existing images. The images were augmented by performing 90° rotation, 180° rotation, 270° rotation, horizontal flip, and vertical flip. After augmentation, the number of images increased to 1.026 for training and 111 images for testing. The result of augmentation image are shown in the Table 2.

D. Training

In this session the data image trained using AlexNet and InceptionV3 model. The image data that is done training is a training set data containing 1,026 images data. This stage we use 10-Fold Cross Validation method to analyze the training data. The image data was training and repeated ten times using 10-Fold Cross Validation approach. The validation data were collected at a rate of 10% from the training data for each running program. The validation data were randomly selected from the training data using the models (AlexNet and InceptionV3) with the same setting. The result of every running from all models were saved and will be used for testing.

To performing the training data, it was necessary to configure the models training setting. Table 3 summarizes the outcomes of the training option setting for AlexNet and InceptionV3.

TABLE III. TRAINING OPTION SETTING

Solver	Adam
Initial Learning Rate	0.0001
Validation Frequency	5
Max Epochs	10

E. Testing

The results of training session are used for testing. In this session the dataset used is dataset testing that amounts to 111 images data. The classifications results were analyzed using performance matrix analysis. This performance matrix results are compared to analyze the performance of two deep learning models AlexNet and InceptionV3 in classification of cervical cell image. The performance matrix is calculated from the confusion matrix graph. For the cervical cell image, we use three classes calculation. The Tables 4 and 5 illustrate the confusion matrix's performance calculation for the three classes [19].

TABLE IV. CALCULATION EACH CLASS OF CONFUSION MATRIX

Confusion Matrix		**Predicted**			**False Negative (FN)**
		Class 1	***Class 2***	***Class 3***	
Actual	***Class 1***	A	B	C	B+C
	Class 2	D	E	F	D+F
	Class 3	G	H	I	G+H
False Positive (FP)		D+G	B+H	C+F	

* True Negative True Positive Misclassified

False Positive False Negative

The calculation was carried out using the confusion matrix findings to acquire the performance matrix values, encompassing accuracy, precision, sensitivity, and specificity. Table 5 demonstrates the calculation.

TABLE V. PERFORMANCE MATRIX FOR CLASS 3

Performance Matrix	Formula	Calculation
Accuracy	(TP + TN)/(TP + FP + TN + FN)	((E+I)+A)/ ((E+I)+A+(C+F)+(G+H))
Precision	TP/(TP+FP)	(E+I)/ ((E+I)+(C+F))
Sensitivity	TP/(TP+FN)	(E+I)/ ((E+I)+(G+H))
Specificity	TN/(FP+TN)	(G+H)/((C+F)+ (G+H))
F-score	2TP/(2TP+FN+FP)	(2*(E+I))/((2*(E+I))+(C+F)+ (G+H))

* TP, TN, FP, and FN each depicts the number of true positives, true negatives, false positives, and false negatives.

III. RESULT AND DISCUSSION

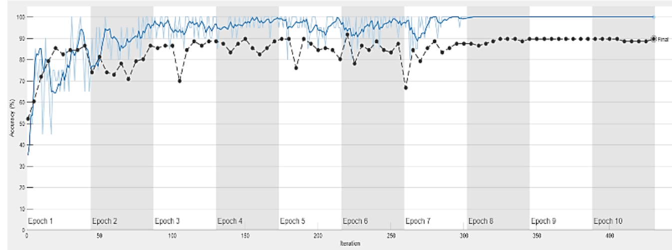
A. Training Result

The data set that is ready to be trained as 10 times running, using each deep learning models. The training result are saved for used to categorize the testing data. After training ten times for each model, we get the value of validation accuracy and training time. The accuracy and the training time for AlexNet and InceptionV3 are shown in the Table 6. The best training graph are displays in the Figure 3. Which Figure 3(a) is the best training result for AlexNet and Figure 3(b) is the best training result for InceptionV3

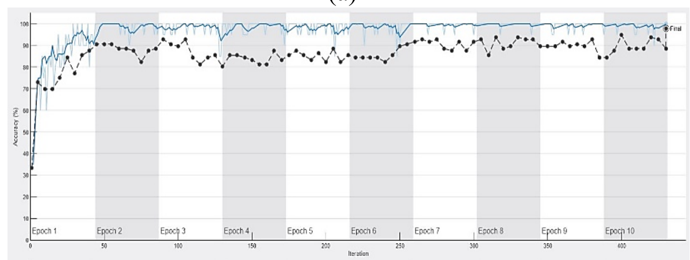
Following the training data results in Table 6, for AlexNet the best accuracy validation obtained a value of 89.29%, with the quickest time being 55 seconds, and the average accuracy validation value of 84.26% ± 3.24%, with an average training time of 57 seconds. For InceptionV3 the best accuracy value is worth 97.92% and the fastest computing value is 10 minutes 50 seconds. The average accuracy for InceptionV3 is 93,93% ± 2,61% with average time is11 minutes 4 seconds.

TABLE VI. TRAINING RESULT

Run	AlexNet		InceptionV3	
	Validation Accuracy (%)	***Time***	***Validation Accuracy (%)***	***Time***
1	85.42%	**55 s**	90,63%	11minute 26s
2	81.25%	60 s	**97,92%**	**10minute 41s**
3	82.29%	59 s	93,75%	10minute 50s
4	80.21%	58 s	93,75%	10minute 59s
5	**89.58%**	**58 s**	97,92%	10minute 50s
6	82.29%	58 s	92,71%	10minute 54s
7	88.54%	57 s	92,71%	11minute 7s
8	82.29%	56 s	94,79%	11minute19s
9	87.50%	57 s	89,58%	11minute 33s
10.	84.36%	56 s	95,58%	11minute 4 s
Mean	*84.26% ± 3.24%*	*57 s*	*93,93% ± 2,61%*	*11minutes 4 s*



(a)



(b)

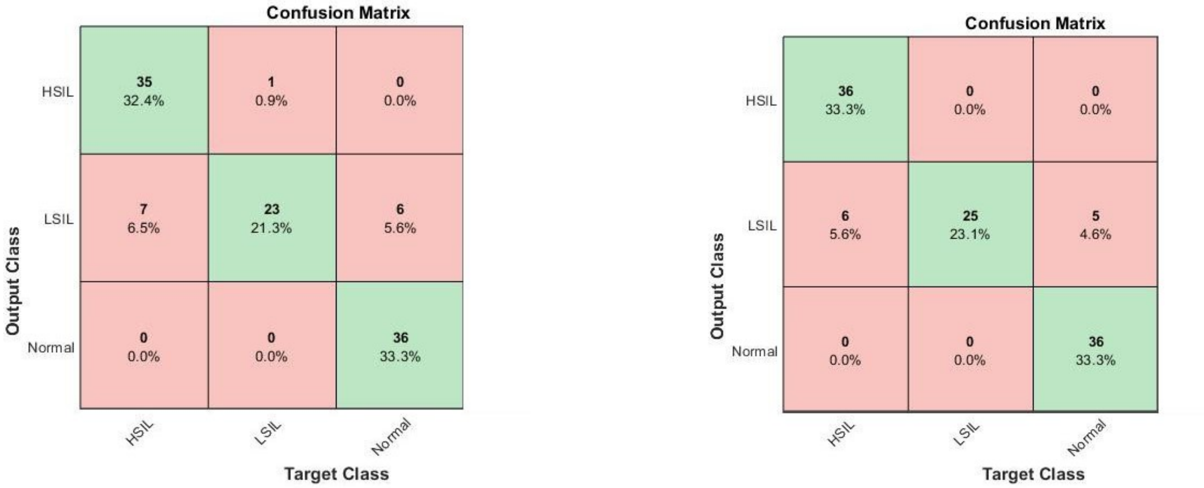
Fig. 3. (a) Training result graph AlexNet (b) Training result graph InceptionV3 (the blue line demonstrates training, and the black line represents validation)

B. Testing Result

After the finish training session, the results of the training are then used to classify the testing data. Then the classifications results were analyzed using performance matrix analysis. The testing outcomes were assessed to determine the performance of the AlexNet and InceptionV3 model on cervical cell image classification. The classification results of cervical cells were assessed using the performance matrix from AlexNet and InceptionV3 model presented in Table 7, with an example of a confusion matrix graph for both models are displayed in Figure 4.

Following the Table 7 portrays the testing result for AlexNet, the best performance matrix for AlexNet model is shown in the sixth running. The best performance matrix result are 89,80% for accuracy, 89,81% for precision, 91,17% for sensitivity, 94,49% for specificity, and 89,26% for F-score. The average values of the AlexNet performance matrix for all running are obtained 80.70%±3.96% for accuracy, 80.59%±3.96% for precision, 80.85%±4.18% for sensitivity, 89.17%±2.30% for specificity, and 79.8% ± 4.03% for and F-score.

The testing result for InceptionV3 that portrait in the Table 7 get the best performance in the running fourth. The best performance matrix results are 89,80% for accuracy, 89,81% for precision, 91,17% for sensitivity, 94,49% for specificity, and 89,26% F-score. The average values of InceptionV3 performance matrix for all running are 82,97%±5,22% for accuracy, 82,91%±5,35% precision, 83,46%±5,70% for sensitivity, 90,46%± 3,25% for specificity, and 82,19% ± 5,50% for F-score.



(a) (b)

Fig. 4. (a) The best Confusion matrix result graph of AlexNet (b) The best Confusion matrix result graph of InceptionV3

TABLE VII. ALEXNET AND INCEPTIONV3 PERFORMANCE MATRIX RESULTS

Run	**AlexNet Model**					**InceptionV3 Model**				
K-Fold	***Accuracy (%)***	***Precision (%)***	***Sensitivity (%)***	***Specificity (%)***	***F-score (%)***	***Accuracy (%)***	***Precision (%)***	***Sensitivity (%)***	***Specificity (%)***	***F-score (%)***
1	77.80%	77.70%	77.02%	87.29%	76.83%	81,50%	81,48%	81,24%	89,65%	80,69%
2	82.40%	80.95%	80.93%	89.75%	80.91%	88,90%	88,89%	89,43%	94,08%	88,53%
3	76.90%	76.85%	76.56%	87.08%	76.39%	89,80%	89,81%	90,45%	94,78%	89,63%
4	78.70%	78.70%	80.93%	87.73%	76.23%	**89,80%**	**89,81%**	**91,17%**	**94,49%**	**89,26%**
5	79.70%	79.63%	79.22%	88.61%	78.91%	79,60%	79,63%	79,21%	88,63%	79,06%
6	**87.00%**	**87.04%**	**88.29%**	**92.88%**	**86.24%**	74,10%	73,53%	74,82%	84,60%	72,65%
7	81.00%	81.48%	81.39%	89.60%	80.51%	77,80%	79,63%	79,33%	88,43%	78,53%
8	82.40%	82.41%	82.35%	90.23%	81.67%	78,70%	76,85%	76,39%	86,92%	76,25%
9	74.10%	74.07%	74.52%	85.62%	73.79%	85,20%	85,19%	86,28%	91,81%	84,30%
10	87.00%	87.04%	87.24%	92.98%	86.54%	84,30%	84,26%	86,29%	91,18%	82,96%
Mean	***80.70% ± 3.96%***	***80.59% ± 3.96%***	***80.85% ± 4.18%***	***89.17% ± 2.30%***	***79.8% ±4.03%***	***82,97% ± 5,22%***	***82,91% ± 5,35%***	***83,46% ± 5,70%***	***90,46% ± 3,25%***	***82,19% ± 5,50%***

IV. CONCLUSIONS

Based on the results of cervical cell image classification using the deep learning models AlexNet and InceptionV3, it can be known that Inception V3 has a better performance compared to AlexNet, this is based on the results of performance matrix analysis of the both models. The best performance matrix results for InceptionV3 are 89,80% for accuracy, 89,81% for precision, 91,17% for sensitivity, 94,49% for specificity, and 89,26% for F-score. However, if we look based on the training time AlexNet have much faster than InceptionV3, with an average training time 57 seconds and fastest training time 55 seconds.

It can be concluded that cervical cell image classification can be done using deep learning models AlexNet and Inceptionv3 as an alternative method for early diagnose of cervical cancer. Which Inceptionv3 is the best model for cervical cell classification and become one of the better options for cervical cancer diagnosis. However, additional testing with other pre-trained models is required to enrich the reference in comparison

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