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Implementation of Siamese Convolutional Neural Network from Cell Images for Malaria Disease Identification

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ABSTRACT

Malaria is contagious and transmitted through Anopheles mosquito. This disease caused about 435,000 people died in 2017. Therefore, it is considered as a dangerous disease. This research aims to implement Siamese Convolutional Neural Network (SCNN) to identify malaria using a collection ofhuman cell images. SCNN is an architecture that uses two convolutional neural networks with the same configurations. Input data for this network are two paired images, where the first is the reference image and the second one is a test image and will produce a similarity score consisting of the numbers 0-1.The data uses in this research is consisted of two classes, namely, parasitized and uninfected. Based on trials that have been carried out, we decide to create SCNNmodel whichis utilizing a pre-trained ImageNet VGG16and a fully connected network with a single hidden layer. Hyperparameter and parameter used are fixed and not all hyperparameter are used. Testing is done by changing the number of reference images and the number of training images. The best accuracy result obtained by using siamese convolutional neural network model is 94.35%.

Key words: Cell Images, Malaria, Siamese Convolutional Neural Network, VGG16

1. INTRODUCTION

Malaria is an infectious disease caused by Plasmodium parasites that live and multiply in human blood cells, and this disease is naturally transmitted through Anopheles mosquito bites [1]. In 2017, an estimated 435,000 people died of malaria globally [2]. In Indonesia, in 2015, the province with the highest mortality rate was Papua, with an Annual Parasite Incidence (API) of 31.93 per 1,000.

Microscopic examination is a technique that often used to detect malaria parasites [3]. Microscopic examination has some limitations, this examination needs a high-quality microscope and it needs an expert who has experienced in using a microscope. The examination also takes around 20-60 minutes to get the result. The quality of the smear affects the results of the examination [4]. With a lack numbers of experts in using a microscope and time-consuming examination, the automation of malaria identification from images is considered as a better option to solve this problem.

Many researchers use deep learning method to classify an image automatically. The purpose of classification is to arrange objects that will be observed into categories that have been defined [5].In [6], researchers used Genetic Algorithm and Deep Neural Network to classify handwritten digits. It only took half time to search a good combination of hidden layers and number of neurons in each layer of the networks. Other researchers in [7] implemented Convolutional Neural Network (CNN) pre-trained model called MobileNetto classify 7 skin disease and able to achieve the maximum accuracy of 94.4%.

In previous studies [8], researchers used CNN to detect malaria. There are 27,578 images used in this experiment and the results came out with97.37% accuracy. Another study using CNN was conducted by [9] to detect malaria parasites and identify species on thin blood smears. This research obtained train accuracy of 94% and validation accuracy of 87.6%. Although CNN gets a high accuracy, this algorithm requires a large number of data and the data needs to be balanced to produce high accuracy. Through a training process that involves a large amount of data, the training process will also require quite a long time. Based on these problems, this research will use Siamese Convolutional Neural Network (SCNN) algorithm. Research conducted by [10] proves that SCNN algorithm is better than CNN algorithm. With 250 data, this research achieved 24.40% accuracy using CNN algorithm while it gets 64.08% accuracy using SCNN.

Siamese Convolutional Neural Network (SCNN) uses a Convolutional Neural Network with the same weight and parameters at each layer [11]. Research on classification using SCNN has been carried out by [12] to detect the alphabet of various languages in the world using omniglot dataset. The best accuracy obtained is 90.61% using a dataset of 150,000. Researchers in [13] conducted other studies using SCNN to do face verification using celebA dataset which consists of 202,599 face images. An accuracy of 85.78% is obtained. Based on a promising result in previous researches, we decided to do some experiment to find the best performance of SCNN for detecting malaria infection in cell images.

2. RESEARCH METHOD

2.1 Dataset

The dataset used is cell imagery with/ without malaria infections, which can be accessed online through the National Library of Medicine (NLM) website in [20].The red blood cell images were obtained from 150 patients infected with Plasmodium falciparum and 50 healthy patients from Chittagong Medical College Hospital, Bangladesh, and collected by researchers from Lister Hill National Center for Biomedical Communications (LHNCBC) which is part of NLM. These images have been manually described by readers of the peripheral blood smear (slides) at the Mahidol-Oxford Tropical Medicine Research Unit in Bangkok, Thailand [14]. The number of images available from the dataset is 27,560 images consisting of 2 classes, namely Parasitized and Uninfected. The dataset has a balanced amount of parasitized and uninfected cases, where each class contains 13,780 images. Figure 1 shows a sample drawing for each class.

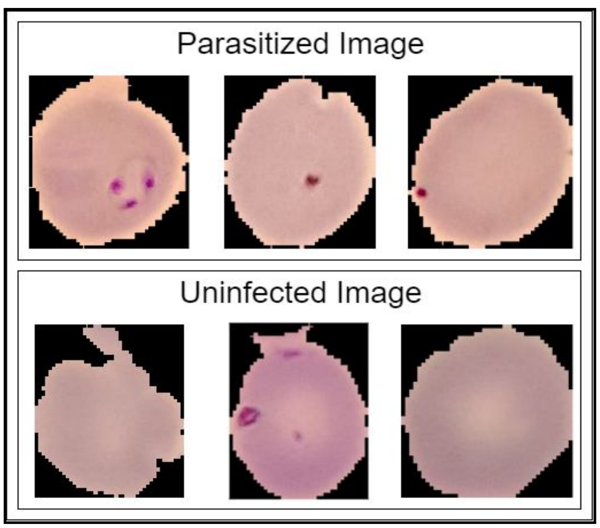

Figure1: Dataset Image

2.2 Convolutional Neural Network

In this study, the CNNpart for our designed SCNN used a pre-trained model with Visual Geometry Group 16 (VGG16) architecture. VGG16 architecture has 16 layers consisting of 1 input neuron, 5 convolution blocks consisting of convolution, ReLu, and max pooling layers, and 3 dense layers [15]. The number of channels from each layer are 64, 64, 128, 128, 256, 256, 256, 512, 512, 512, 512, 512, and 512. Figure 2 shows the architecture of VGG16. By using the pre-trained model implementation provided by Keras, the pre-trained model is used as a feature extractor without an extra CNNfine-tuning process [16].

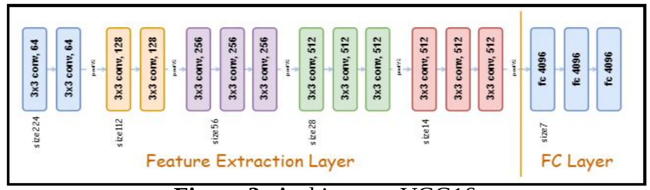

Figure 2: Architecture VGG16

2.3 Siamese Convolutional Neural Network

Figure 3 described SCNN architecture that will be used in our experiments. This network received a pair of 224x224 cell images as an input. Later, such input will be fed into a pre-trained ImageNet VGG-16 and resulting image features foreachinputimage[17]. Each of image extracted features then will be transformed into one dimensional array with a flattening function. Next, the Manhattan distance function is used to find out the similarity of the two image extracted features by calculating the distance between them [18]. The Manhattan distance function is given by the following equation,

$$dist(x, y) = \Sigma_{i=0}^{n} |x_i - y_i| \#(1)$$

where$x$ and y is a sequence of numberswith the same length of n.

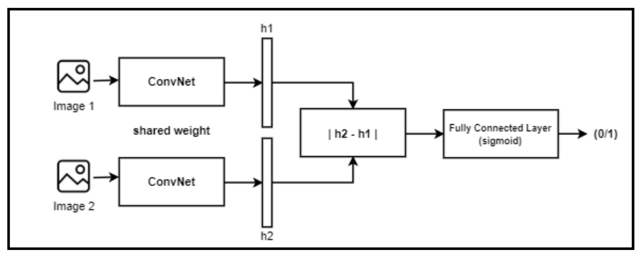

Figure 3: Flow Siamese Convolutional Neural Network

Later, the calculation results will be used as an input of the fully connected networks with a single hidden layer which consist of 512 neurons and a single neuron in the output layer. The hidden layer in the proposed architecture is using Rectified Linear Unit (ReLU) as an activation function. Besides, the sigmoid activation is used for the output neuron to bound the yielded output in range of [0,1] [19]. The Equation 2 shows the definition of sigmoid function.

$$f(x) = \frac{1}{1 + e^{-x}} \#(2)$$

2.4 Splitting Dataset

In this research, we split the dataset into training and testing sets with ratio of 3:1. This training and testing data will each be used for the image pairing process. In our experiment, we declare a N_data variable to control the amounts of training data used and use 6.890 data as a testing data.

2.5 Pair Creation

Figure 4 shows a set of pairs that will be fed into the network. For the pair creation process, first, N_way reference image for each class (parasitized and uninfected) is selected randomly from the training dataset. Later, for each class, by each selected reference image, we paired the selected image with every other image in the training set and give them a label of one when they have the same class and label of zero otherwise. Figure 4 shows a resulting group of pairs yielded by the pair creation process.

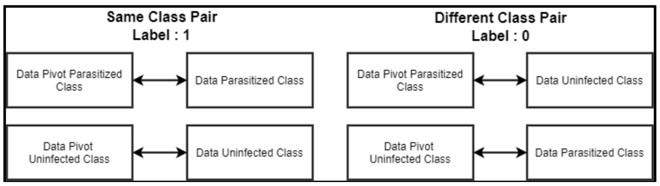

Figure 4: Example of Pair Creation Process

When N_way is set to$n$, the pair creation process will be resulting $2 * n$ group of training sets as we need to select N_way of uninfected and N_way of parasitized reference images

2.6 Training

Based on the previous step, the training process will be carried out for each group of training sets. Therefore, for N_way of n, there will be in total$2 * n$ classifiers trained. In the training process, each classifier is trained by the use of initial learning rate of 0.001,Adam as a learning rate optimization algorithm, epochs of 50 and batch size of 32.When the training process is done, each trained classifier and its reference image will be saved for further steps.

2.7 Testing

Testing process is carried out for each class. After these processes are completed, a consensus process is carried out to determine whether the predicted results are correct. Since the result is coming from N_way * 2 reference images, we gathered all the label results and used consensus process. There are three kind of consensus processes that are used in this paper, namely, voting, maximum and average. Figure 5 shows the explanation of voting, maximum, and average consensus.

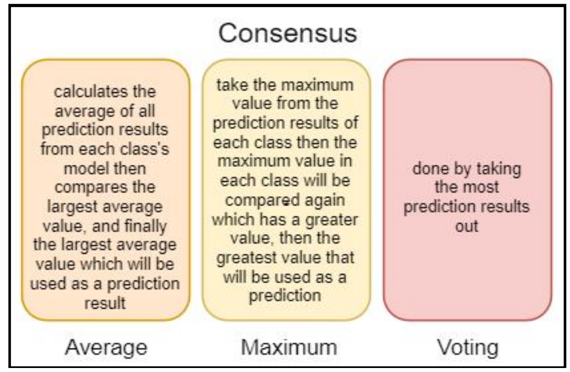

Figure 5: Consensus Explanation

After this process, the number of correctly classified data generated from the consensus process is used to calculate accuracy. Calculation of accuracy can be done by dividing the amount of data that is classified correctly with the total sample of testing data to be tested [19]. Equation 3 shows how to calculate accuracy.

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \#(3)$$

where:

TNare True Negatives
TPare True Positives
FN areFalse Negatives
FPare False Positives

3. EXPERIMENT AND RESULT

In this section, we tested CNN and SCNN model to get the best combination of N_way and N_data value that can give better accuracy. We also compared the accuracy between these two models.

3.1 SCNN Model

In SCNN model, the model is again carried out the training process using the amount of data and the number of different models by using the values of N_way and N_data variables. The values of N_wayare 1, 2, 4, 6, 8, 10 and the values ofN_dataare 100, 200, 400, 600, 800, 1,000.Figure 6 shows the accuracy when we applied different N_way values when N_data is 100.

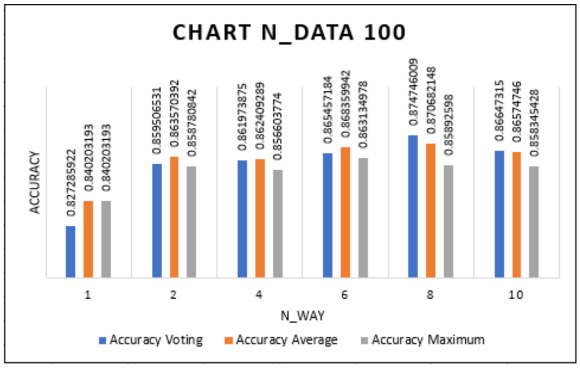

Figure 6: Chart prediction results N_data 100

Figure 7 shows the accuracy when we applied different N_way values when N_data is 200. It can be seen that overall accuracy is increasing.

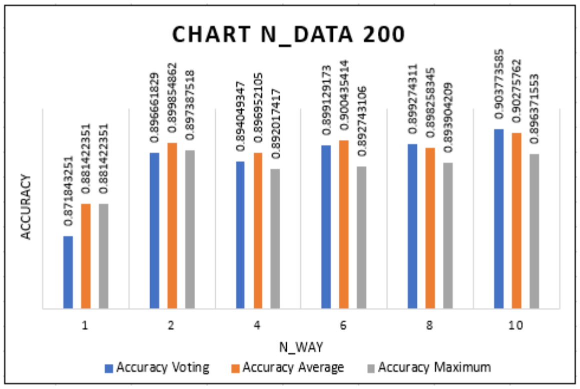

Figure 7: Chart prediction results N_data200

Figure 8 shows the accuracy when we applied different N_way values when N_data is 400. The accuracy reaches more than 90% for each N_Way values.

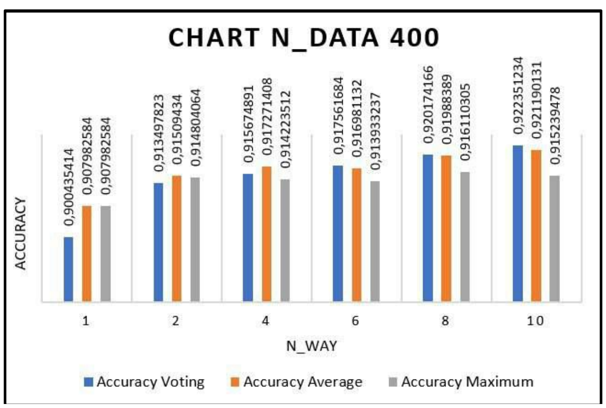

Figure 8: Chart prediction results N_data400

Figure 9, 10, 11, and 12 shows the accuracy when we applied different N_way values when N_data is 600, 800, 1000, and 20688, respectively.

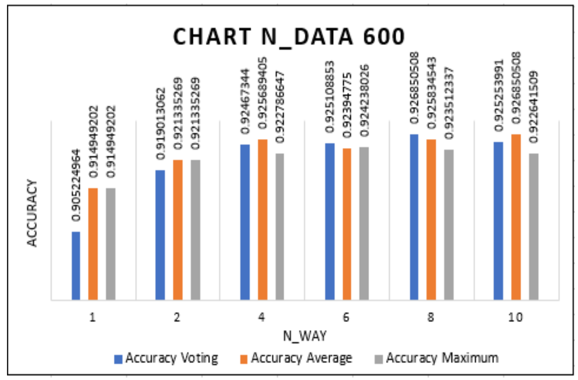

Figure 9: Chart prediction results N_data600

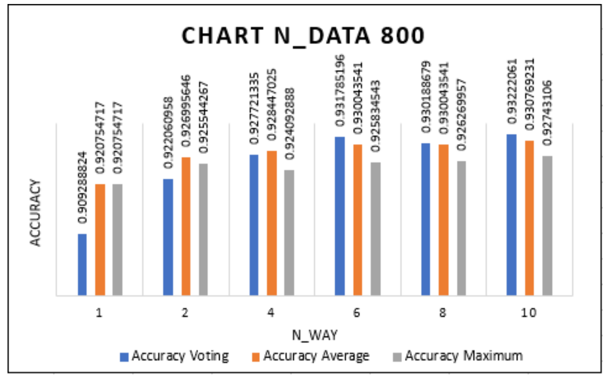

Figure 10: Chart prediction results N_data800

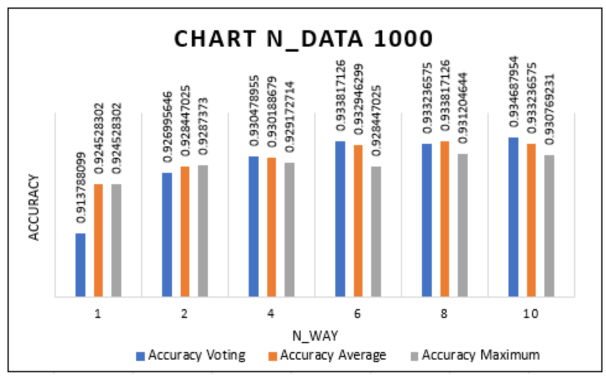

Figure 11: Chart prediction results N_data1000

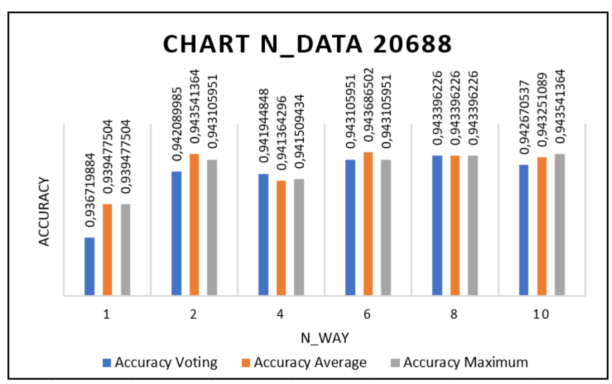

Figure 12: Chart prediction results N_data20668

From N_data 100 to N_data 1000, we can see that the accuracy is slightly increased. Voting consensus is slightly better compared to the other consensus methods with respect to the prediction accuracy yielded. Furthermore, we can conclude that the accuracy is increasing with the greater value of N_data used. Moreover, in Figure 12, when N_data is set to 20,668, maximum consensus is better than other consensus methodsas its experiment result reached the highest accuracy. But, if we compare with the results from Figure 11, the increasing value of accuracy is not significant since it is only increased by 0.01 while the data used is 20 times bigger.

3.2 CNN Model

At this section, we show the comparison between CNN and SCNN model. Figure 13 shows the accuracy results from each N_data values. It can be seen that the accuracy of SCNN is slightly higher than CNN when the N_data is 20.668. However, SCNN outperformed CNN when the provided N_data is relatively small. As can be seen in Figure 13, SCNN still has yield a better accuracy score even when the provided data is relatively small.

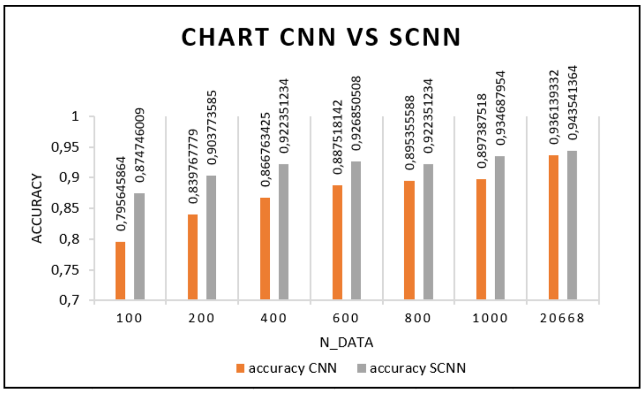

Figure 13: Comparison chart of CNN and SCNN accuracy results

4. CONCLUSION

In this work, we propose cell imaging classification via similarity learning using multiple siamese convolutional neural network (SCNN). The SCNN architecture was build using pre-trained ImageNet VGG16 architecture. Based on the evaluation of the resulted model using 6,890 testing data and various combinations of N_way and N_data values, with greater N_data, the resulted model able to achieve significantly better accuracy.Compared to the regular CNN approach, when the provided dataset is considerably small, multiple SCNN model can still produce a relatively high accuracy(ranging from 87-93% for dataset with the size of 100 to 1000). Finally, in our experiment, the best accuracy score is obtained by the SCNN model is 94.35% when we trained multiple SCNN model using N_data of 20668 and N_way of 10 with maximum consensus technique.

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