Classification of Cervical Type Image Using Capsule Networks

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***Abstract*—Cancer is one of the most lethal disease in the world. Therefore, early treatment of cancerous patient is proofed effective to decrease the lethal rate of this disease. For example, is cervical cancer, the precancerous step of cervical cancer is detected by looking at the cancerous transformation zone on the cervix. Furthermore, there are some different type of cervix regarding to its transformation zone. Therefore skills and experience is needed to be able to precisely determine which type of cervix making detection of cervical cancer is less efficient. This study is creating a deep learning model based on Capsule Networks to classify colposcopy images as a solution to make cervical cancer detection and treatment more effective and efficient. With a result of 100\% accuracy of the test set and 94.98\% accuracy of the train set. This study exceeds the result of other earlier experiments**

Keywords—bee colony optimization, nurse rostering problem, metaheuristic, swarm intelligence

I. INTRODUCTION

Cancer is one of the most dangerous diseases in the world. With statistical data showing 18.1 million new people contracted cancer and 9.6 million deaths from cancer in 2018 [2]. For example, cancer of the cervix which ranks second as a cause of death from cancer in women aged 20 to 39 years, has 13,240 new cases in 2018 [5]. However, early treatment of patients who have been resurrected proved very effective in reducing the rate of death from this cancer. Cervical cancer is one of the cancers that is easily prevented if it has been detected in the pre-cancer stage [1]. With the help of technology now the diagnostic process is expected to develop rapidly..

Focusing on cervical cancer, to be able to detect cervical cancer, there are several stages that must be carried out. (World Health Organization) recommends three steps that include a pap smear, colposcopy, and biopsy techniques [6]. The most commonly used method is pap smear, which is taking cells from the cervix and doing in-depth analysis by experienced doctors handling and analyzing these cells, but this conventional method still has a diagnostic error of 50% negative cancer results.

The second stage is colposcopy, a method where expert medical personnel looks directly at the condition of the cervix by using a device called a colposcope and see if there are injuries or abnormalities in the cervix. On the colposcopy examination, the medical staff will see the transformation zone in the cervix. But not all the cervix has a zone of transformation that is immediately visible. There are several types of the cervix with different areas of transformation.

There are 3 types of cervix classification based on the location of it's transformation zone. Type 1 is the type of cervix where the transformation zone is located in the outside of the Cervix (ectocervical). This type transformation zone can be seen as a whole and have no area that was hidden.

Type 2 Cervix has most of the transformation zone in the outside area of cervix, also it has some of it's transformation zone hidden in the inside of the cervix (endocervical). While Type 3 cervix has most of it's transformation zone in the inside area of the cervix (endocervical), and most of it are hidden. This type may have only a little portion of it's transformation zone visible, or may have it's whole transformation zone hidden. The illustration for transformation zone location can be seen in Figure 1.

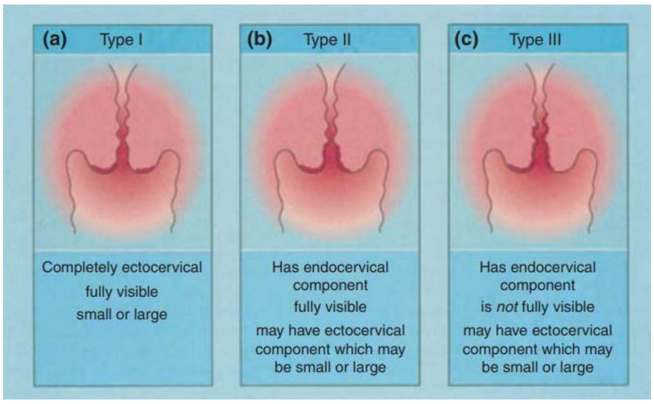

Fig. 1. Illustration of cervix classification based on transformation zone

Why is cervical type classification considered necessary because most cervical cancers start from cells in this transformation area, where the transformation area in cervix type 2 and type 3 allows for hidden changes that require different diagnostic and treatment techniques [3].

This causes some patients who need further testing. Decision making based on the type of cervix is considered very important for patients so that each patient gets the right treatment [3]. But to be able to determine the type of cervix appropriately requires high experience and expertise from staff on duty. This is an obstacle in the early detection of cancer, especially in some developing countries and areas that are still remote. So the diagnostic aids need to be developed.

At this time the deep learning classification method is attracting attention because it is able to break through the limits that are owned by CNN is the Capsule Network introduced by Hinton et al in 2017 [4]. Where there is a significant raise in some specific dataset that capsule network can achieve higher accuracy than CNN. The most simplified explanation of the differences is while CNN can also detect features in an object, Capsule network bring it to another step that it can detects features in an object alongside it’s orientation and position. Makes it more accurate than CNN.

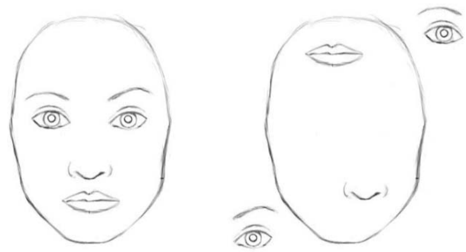

Fig. 2. Illustration of feature detecting of a face [4]

This image represents a perfect condition that differentiates Capsule Networks and other Neural Networks, in Figure 2 there is two images, the left image is a face, while the right side is a disoriented face. Neural Networks recognizes these two images as face, because both images have same feature despite of its orientation. Capsule Networks only detect the left image as a face because it knows that the right images is disoriented.

Further supporting evidence is a research conducted by Zhang et al, that has an accuracy that exceeds other existing models such as Artificial Neural Network, ResNet, and others [7]. That makes up for the reasons that this research focuses on the use of a Model based on the Capsule Network to classify cervical types on cervical coloscopy images.

II. Developed Models

As explained earlier, the type of cervix is very influential in the details of the diagnosis of cervical cancer. To be able to make an accurate diagnosis requires high expertise and experience from the medical staff or doctor in charge. This obstacle also inhibits the process of detecting cervical cancer early in remote areas.

So that we need an assistive device to classify the type of cervix. Which will be used is a deep learning model called Capsule Network where this model will be trained by using images from the results of coloscopy which later this model will be able to classify the type of cervix owned by the patient. Data sets that will become training data and test data are also limited to data prepared by Kaggle.com which had held a competition for cervical classification classes. Where the data set numbered about 6000 images from the collection of coloscopy. These data and methods have been investigated by Zhang et al [7] but still experience overfitting constraints resulting in less than optimal accuracy.

A. Dataset

The dataset used for the current study is data provided by Kaggle.com in the Intel / MobileODT Cervical Cancer Screening petition which contains 8141 colposcopy images in the *.JPG* format, with the largest image sized 4128x3096, divided into 3 categories (1431 images of Cervical type 1, 4306 images of cervix type 2, 2404 images of cervix type 3). Samples of the dataset can be seen in Figure 2.

Fig. 3. Example of Cervix images, Type1, Type 2 and, Type 3 respectively

Furthermore, the data is reduced so it will have the size of 32x32 pixels. Data augmentation is done to provide more data in order to avoid overfitting during training. From 8139 images provided, they were rotated with a margin of -20% to 20% also getting a horizontal image reversal. This data augmentation is carried out randomly in each image category and arranged to produce a total of 42992 images with almost the same amount of data in each category. Resulting images that have been augmented can be seen in Figure 4. This dataset is divided into 90% as the training dataset, 5% as the validation dataset and 5% as the test dataset.

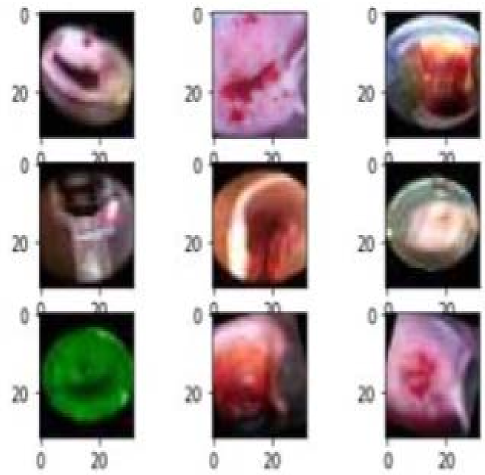

Fig. 4. Sample result of augmented dataset

B. Caps-Net Model Architecture

Capsule Network is a new model in deep learning that was discovered by Hinton et al in 2017. The basic idea of the Capsule Network architecture has been expressed a few years before that, but Clinton was only able to complete the model in 2017.

The following is an explanation of the capsule network explained by Sabour et al in his journal. A capsule is a group of neurons that represent several parameters, and the length of this vector indicates the possibility of a specific entity. So that the Capsule network can know the existence of an entity not only based on the presence of its features but also on the orientation of the features that build the entity [4].

The Capsule Network that was built in this study is divided into 6 layers. The first is the input layer which holds 32x32x3 images. Followed by the first convolution layer with 256 filters and 9x9x3 kernel size, stride value of 1, and use the RELU activation function.

The next layer is the PrimaryCapsules layer consisting of 2 parts, namely convolution with a 5x5x256 kernel, stride value of 2, then the second part converts scalar to vector with the reshape function producing 1600 capsules with 16D. The last layer of the CervixCaps layer consists of 3 capsules with a size of 32. The architecture of the model built can also be seen in the following Table 1. In this step that routing between Capsule Algorithm is implemented to Specify which entity belongs to one of the three class of images.

TABLE I. CAPS-NET MODEL ARCHITECTURE

Layers	Input Size	Output Size
Input Layer	(-,32,32,3)	(-,32,32,3)
Conv1 Layer	(-,32,32,3)	(-,24,24,256)
Primary Caps (Conv)	(-,24,24,256)	(-,10,10,256)
Primary Caps (Reshape)	(-,10,10,256)	(-,1600,16)
Cervix Caps	(-,1600,16)	(-,3,32)
Output Caps	(-,3,32)	(-,3)

C. *Experiment*

The model that has been built is then trained using learning rates of 0.0001. A total of 50 Epochs with a batch size of 215. And the model will be validated at each end of each epoch. After the model has been trained, the model is tested using a test dataset with a batch size of 10.

The model was trained and tested in a computer device with 16GB RAM specifications, AMD Ryzen 5 1600 Pro-processor, NVIDIA GeForce GTX 1050 Ti Graphic Card, using Python 3, GPU-based Hard + TensorFlow and Windows 10 operating system.

III. RESULTS AND DISCUSSION

This developed model was trained with the prepared dataset for approximately 1 hour and two minutes, From those duration the result of training process can be seen in Figure 5 and Figure 6.

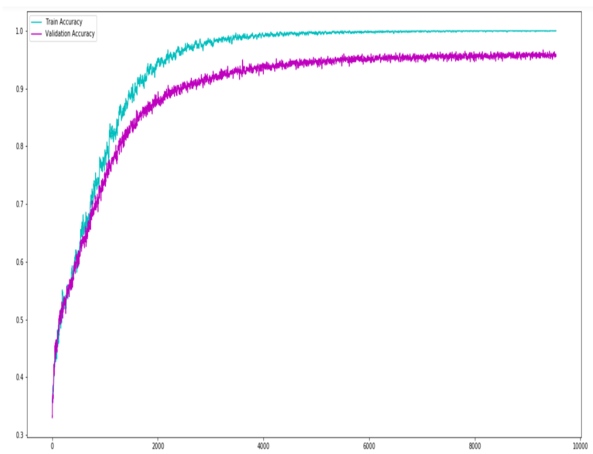

Fig. 5. Accuracy of train dataset and validation dataset

From this figure, it can be seen that the Accuracy of the training process start to peak and stabilize after training the 6000 batch mark. While the validation set accuracy start to reach the peak at almost the same mark, the validation set didn’t stabilize as much.

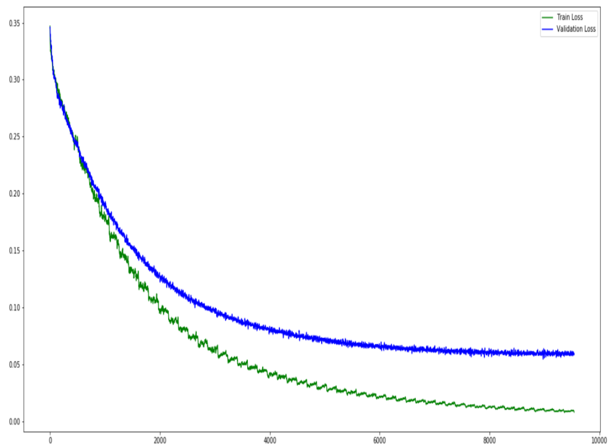

Fig. 6. Loss of train dataset and validation dataset

This Figure 5 shows that the loss of training set reach the peak almost at the end of the training process while the validation set start to get it lowest loss value at the 6000 batch mark, almost the same time it gets the highest accuracy value.

The results of the accuracy of the model that was made can be seen in Table 2. The calculated loss is the overall margin loss. It was calculated using the margin loss sum function in the TensorFlow module. Comparative results obtained in previous studies can be seen in Table 3. The Confusion Matrix for 2150 test data can be seen in Table 4.

TABLE II. CAPS-NET TEST RESULT

Train accuracy	Validation Accuracy	Validation loss	Test Accuracy	Test Loss
100%	95.02%	0.060647525	94.98%	0.05863982

Table 2 shows the best result after the training process and then the network is tested using the Test set that was already prepared before.

TABLE III. COMPARED RESU;T FROM PREVIOUS EXPERIMENT

Model	Train Accuracy	Test Accuracy
CapsNet-cervix model[7]	99%	80.1%

Table 3 shows the result from previous experiment done by Zhang et.al, while the train set accuracy already peaked, it gain different test set accuracy result. That is lower. At 80.1%

TABLE IV. EXPERIMENT CONFUSION MATRIX

	Prediction 1	Prediction 2	Prediction 3
True 1	0.33488372	0.00372093	0.0027907
True 2	0.00418605	0.29069767	0.02232558
True 3	0.00186047	0.01534884	0.32418605

The data consist in Table 3 shows where the trained Network get confused at, the network get more confused in the process of differentiating type 2 cervix and type 3 cervix, where the wrong prediction of type 2 cervix as type 3 is at 0.279 % of the test set, and the wrong prediction of type 3 cervix as type 2 is at 0.153% of the whole test set.

From the results of the study, it took about 1 hour and 2 minutes to conduct training data. This time is faster than previous research. Due to not doing the segmentation step which also requires the training process.

The results of the study also showed an accuracy of 94.98% for testing data and approaching training data accuracy and data validation, which means this model can pass overfitting problems that occur in previous studies. previous studies only reached 80% accuracy. According to the author's analysis, the accuracy in this study is probably caused by not doing segmentation on the data set used. So the capsule network model can identify the features of each type of cervix as a whole image. The possibility of missing features due to the effect of segmentation is what causes differences in the achievement of accuracy between the two models made.

IV. Conclusion

The model for the classification of cervical types has been successfully carried out. Tests using the Cervical Cancer Screening dataset indicate that the proposed model can produce up to 94.98% accuracy and compete with research using a similar method with an accuracy rate of 80.1%. The accuracy of this model can be improved by developing a more in-depth architecture, as well as making better hyper-parameters and using a larger quantity of datasets. This study gives good results and can be used to effectively classify cervical types with an error rate below 6%.

Acknowledgment

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