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Colorectal Polyp Detection Using Feedforward Neural Network with Image Feature Selection

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***Abstract*—Colorectal cancer is one of the most common cancers in the world and accounts for approximately 700,000 deaths annually. Early detection is one of the keys to detecting polyps before transforming into malignant colorectal cancer. Along with the development of computing technology, there are many techniques utilizing image processing and computing algorithms method to identify the polyps due to increased data processing speed and also faster computational algorithms. Polyp detection is a very challenging problem because polyp detection involves many factors. This research tries to perform a new improvisation in polyp detection process in terms of pre-processing stage and classification stage by utilizing statistical feature selection technique from collection bag of features combined with feedforward neural network methods. Based on experiments that have been done it is found that the proposed method is able to provide the accuracy on polyp detection at 97.85% with 6-(12)-2 neural network architecture.**

***Keywords*—colorectal; polyp; feature; selection; neural; network**

I. Introduction

Colorectal cancer is one of the most common cancers happened in the world population [1] and accounts for approximately 700,000 deaths annually [2]. The percentage of colorectal cancer patients reported increases every year [3]. Colorectal cancer is a type of cancer begins with the growth of abnormal tissue in the human intestinal mucous membrane. Abnormal tissue resembles the plastic point that grows on the human mucous membrane called polyp. Studies that have been carried out by [4] on the case of polyp tissue growth in the human body, suggest that more than 90% of polyps have three millimeters in diameter. If the size of the polyp growth exceeds than three millimeters, it is certain that the polyp can be turned into malignant cancer in the future [5] [6].

Early detection is one of the keys to detecting polyps before transforming into malignant cancers. In the medical world, endoscopic screening is a common practice to identify the presence of polyps in the human intestine. The output of endoscopic screening is a digital medical image. Manual or visual techniques to interpret endoscopic screening medical image performed by endoscopist experts have many limitations, such visual interpretation is time-consuming and influenced by the level of expertise of an endoscopist in translating or recognizing polyps in endoscopic images [1] [5]. Visual interpretation also cannot be separated from human-eye error. Given these limitations, manual or visual interpretation of the endoscopic image may resulted decrease of accuracy, specificity, and subjectivity in polyps detection processes [7]. In the other hand, the accuracy of polyp detection has great importance, since the identification of polyps become the basis of the patient's prognosis and closely related to the treatment recommendations that the patient should receive [8].

However, in addition to the previously described limitations, there are other limitations such lack of endoscopic experts who are truly experts in identifying polyps [9], the cost to interpret endoscopic scans is also quite expensive besides train a new endoscopist is even more costly. To overcome the weakness of visual or manual image interpretation on an endoscopic image result, there need to build a computerized system that applies the methodology of digital image processing that supports the polyps identification carried out by the endoscopist. Because, an endoscopist is expected to accurately detect polyps so as to provide a correct prognosis and treatment to the patient.

Along with the development of computing technology, there are many techniques utilizing image processing method also computing algorithms to identify the polyps, due to increased data processing speed and also the faster speed of computational algorithms [10]. In relation to polyp detection, research [1] carried out detection processes using a model of spectral medical image analysis technique combined with machine learning. Spectral analysis was done by applying the Empirical Mode Decomposition (EMD) method to obtain the polyp feature. Machine learning method named Least Square Support Vector Machine (LS-SVM) is used to select the features resulted from spectral extraction and LS-SVM also play a key role in polyp detection. In the process of detection, research [1] used the Bayesian Network classifier function and obtained 99.09% detection accuracy. Research [11] uses curvature-based morphology extraction techniques, fractal dimension, and volumetric feature maps to detect polyps in CT Colonography images. With the use of morphologic-based image extraction, research [11] succeeded in decreasing the average false-positive detection rate by 52.4% and obtaining high detection sensitivity value at 96.2%, to detect polyps that have a size larger than 5mm.

The signal processing technique such discrete wavelet-based transformation is used by research [12] to detect the presence of

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polyps in the human gut, based on gastroenterology video datasets obtained from the American College of Gastroenterology. Research [12] carried out the feature extraction process by applying the wavelet transformation technique followed by the edge detection techniques. Principal Component Analysis (PCA) is also applied by research [12] to reduce feature dimension resulted from the output of the wavelet transformation process and edge detection. In the process of polyp classification and detection, research [12] uses the Synthesize Similarity Measure (SSM) method to overcome calculation errors caused by illumination disorder, surface or geometrical view blur that often occur in Gastroenterology video. With the application of Synthesize Similarity Measure (SSM) technique, research [12] obtained a high polyp detection accuracy of 98.82%.

Caused by the highly considerable variation of the shape, color, texture, and size of the polyp, and the difficulty of finding the distinction between polyp classes, research [13] proposed a method to detect polyp colonoscopy videos by utilizing three-dimensional extraction approaches and Convolutional Neural Network. By using spatial down-sampling of the width × height × length × channel characteristics in colonoscopy videos, research [13] formed six Convolutional Neural Networks (Conv) layers with sizes of 3 × 3 × 3, each of the Convolutional Neural Networks layers followed by the linear rectifier units. The backpropagation algorithm used by [13] in the training phase and obtained a detection accuracy value of 98.7%. Despite the difficulty in detecting polyps based on shape characteristics caused by high variations of shape data, research [14] managed to obtain a high polyp detection sensitivity value by 88.0%. In addition, besides using image shape characteristics as the basis of the detection, research [14] also integrates specific polyps context characteristics in the form of vessels boundaries, specular of spots, and lumen areas, that can be found in each image of colonoscopy dataset that obtained from CVC-ColonDB.

Based on the previous research which has been described, it can be concluded that polyp detection is a very challenging problem because polyp detection processes involves many factors [15] which can affect the accuracy of detection, whether it is seen from the side of image instance such as shape, color, texture, and size of polyp or from the side of the detection method that used to. Based on research [16] which has conducted a survey on the approaches that have been used to detect polyps, they concluded that the accuracy of polyp detection can be improved by doing some improvements in the pre-processing-stage, feature extraction-stage, classification-stage or in all, this study attempted to perform a new improvisation in the polyp detection process from the pre-processing-stage and classification-stage.

Improvisation of the pre-processing stage is accomplished by utilizing statistical selection techniques on a collection of a bags of features resulted from the extraction of image shape and image texture. From the side of classification stage, this research does an improvisation by utilizing feedforward neural network classifier. From this research, it is expected to result in a lightweight polyp information retrieval system with a minimal requirement of the computing resource, which also can assist novice endoscopist to educate themselves in recognizing polyps and support the knowledge that has been studied from the knowledge that provided from experienced endoscopists.

II. Polyp Detection Approach

The proposed work of colorectal polyp detection applying feedforward neural network and selected image features involves steps follows as seen on Fig.1.

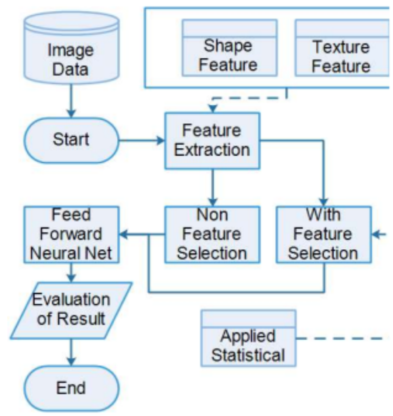

Fig. 1. Steps of proposed colorectal polyp detection

A. Get Polyp Dataset

First, we collected for about 100 colon-polyp image dataset and 100 colon-normal image dataset in .jpg format with 520x480 pixel resolution resulted from colon endoscopy processes taken by endoscopist at Sardjito Regional Public Hospital, Yogyakarta, Indonesia. The example of colon-polyp presented on Fig. 2.

B. Image Feature Extraction

In this proposed work, we extract image feature based on image shape and image texture. Feature shape image used in this research is:

- Roundness. Reflects the value of the comparison of the foci ellipse minor with the foci ellipse major of an object in the image. A roundness calculation that yields a value between 0 and 1, is presented on (1).

$$\sqrt{1-\frac{b^2}{a^2}} \tag{1}$$

where e = roundness, b = ½ value of object's heights in the image, and a = value of the object's width in the image.

- Aspect ratio. Reflects the value of the comparison between the height and width of the object in the image.
- Triangle. Reflects the comparison between the object area in the image to the overall image area.

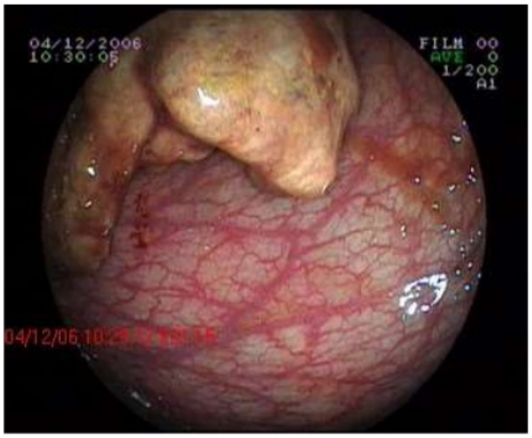

Fig. 2. Colon-polyp example image.

The example of colon-normal image dataset presented on Fig. 3.

Fig. 3. Colon-normal example image.

The extracted image texture information includes:

- Contrast. Express the local variable values of the image. Contrast is a comparison between the background and foreground values [16]. Contrast showed in (2).

$$\sum_{i,j} |i-j|^2 \, P(i,j) \tag{2}$$

- Correlation is a linear measure of the gray level in neighboring pixels [11], [17]. Correlation showed in (3).

$$\sum_{i,j} \frac{(i-\mu_i)\,(j-\mu_j)\,P(i,j)}{\sigma_i \sigma_j} \tag{3}$$

- Energy. Reflects the uniformity of pixels in a single image. Since higher energy value in the image can make the image texture more uniform [18]. Energy showed in (4).

$$\sum_{i,j} P(i,j)^2 \tag{4}$$

- Homogeneity states the measure of proximity of gray level element in co-occurrence matrix [19]. Homogeneity showed in (5).

$$\sum_{i,j} \frac{P(i,j)}{1+|i-j|} \tag{5}$$

Where P $(_{i,j})$ i, is the i_{th} row element and the j is the j_{th} column of the co-occurrence matrix. μ_i is the average value of the i_{th} and μ_j is the average value of the j_{th} column in the matrix P. σ_i is the value of standard deviation of the i_{th} row and σ_j is the value of standard deviation of the j_{th} column in the matrix P [19] [20].

C. Image Feature Selection

The feature selection processes apply statistical techniques called independent t-Test [21] to select features that obtained from shapes and textures extraction processes. Independent t-Test used to find image feature that is closely interconnected with each other and serve as the basis to distinguish between colon-normal images and colon-polyp images. Independent t-Test testing involves two types of hypotheses [21]:

1) *Hypotheses (H0)* is defined by a significant similarity of features between colon-normal image and colon-polyps extraction result.
2) *Hypotheses (H1)* is defined as the absence of a significant similarity of features between colon-normal image and colon-polyp image extraction result.

The resulting feature of Hypothesis (H1) with a significance value of <0.05 has the meaning that the feature can really serve as the basis of the distinction between colon-normal and colon-polyp image [21]. The selected feature becomes Feedforward Neural Network input. The feature selection processes are expected to increase the value of detection accuracy.

D. Feedforward Neural Network

Although there are various types of training algorithms Neural Network [22] [23]. In this study, we use the Quasi-Newton training (trainlm) algorithm [24], arguing that the Quasi-Newton (trainlm) algorithm is capable to produce faster training time and optimal learning result compared to other training algorithms [24] [25]. In addition, due to the lack of certainty regarding the number of best-fit neurons in the hidden layer that can be used to solve problems with Neural Network [26] [27], this study does some neuron numbers variation in the hidden layer. The proposed Neural Network architecture can be seen in Table I.

On the other hand, we also form the Feedforward Neural Network architecture of non-selected input feature with the input of 7 neurons as a comparison to Feedforward Neural Network with selected input feature. As presented in Table II.

TABLE I. FEEDFORWARD NEURAL NETWORK ARCHITECTURE SELECTED INPUT FEATURE

No	Feedforward Neural Network Architecture		
	Input Neurons	***Hidden Layer Neurons***	***Output Neurons***
1.	According to Feature Selection	3	2 (polyp/normal)
2.	According to Feature Selection	6	2 (polyp/normal)
3.	According to Feature Selection	12	2 (polyp/normal)

TABLE II. FEEDFORWARD NEURAL NETWORK ARCHITECTURE NON-SELECTED INPUT FEATURE

No	Feedforward Neural Network Architecture		
	Input Neurons	***Hidden Layer Neurons***	***Output Neurons***
1.	7	3	2 (polyp/normal)
2.	7	6	2 (polyp/normal)
3.	7	12	2 (polyp/normal)

E. Evaluation of Result

Accuracy and mean-squared error (MSE), is used in this research to evaluate system performance in detecting polyps. The following is an explanation of each of the evaluation parameters used in this research.

1) *Accuracy* is the ratio between the actual result of recognition colon-polyp image and colon-normal image compared to the overall image data with desired output pattern.
2) *Mean-squared error (*MSE*)* reflect an absolute error of Feedforward Neural Network output pattern compared with desired output pattern.

III. RESULT

The experiments in this study were carried out in the Matlab 2015R IDE environment and the IBM SPSS Version 21 running on the Windows 10 Enterprise 64-bit operating system. Experimental image datasets include 100 colon-normal images and 100 colon-polyp images.

A. Image Feature Extraction

In the pre-processing step, all images are converted into grayscale to simplify the computation process [28] to further execute feature extraction processes based on shapes and textures. To shorten the writing, here are some examples of shape feature extraction results as presented in Table III.

TABLE III. IMAGE SHAPE EXTRACTION RESULT

Image	Roundness	Aspect Ratio	Triangle
Colon Polyp-1	7.117717	0.714487	0.643960
Colon Polyp-2	9.679821	0.830967	0.665481
Colon Polyp-3	6.793475	0.472521	0.652688
Colon Polyp-4	8.664244	0.860054	0.719874
Colon Polyp-5	4.272532	0.855398	0.770894
Colon Normal-1	6.665990	0.969178	0.718101
Colon Normal-2	1.157262	0.952862	0.834684
Colon Normal-3	3.870675	0.992933	0.744464
Colon Normal-4	1.755050	0.952862	0.828485
Colon Normal-5	2.332724	0.786103	0.776929

Image texture selection result are presented on Table IV.

TABLE IV. IMAGE TEXTURE EXTRACTION RESULT

Image	Contrast	Corre-lation	Energy	Homo-geneity
Colon Polyp-1	0.420779	0.936981	0.718793	0.974660
Colon Polyp-2	0.257085	0.972151	0.659860	0.976365
Colon Polyp-3	0.252122	0.978325	0.615894	0.974392
Colon Polyp-4	0.151781	0.983110	0.484922	0.973266
Colon Polyp-5	0.127858	0.984600	0.419923	0.970247
Colon Normal-1	0.152218	0.979548	0.229781	0.958250
Colon Normal-2	0.154342	0.976709	0.184114	0.951917
Colon Normal-3	0.173680	0.986271	0.233853	0.961678
Colon Normal-4	0.187677	0.973839	0.184352	0.951189
Colon Normal-5	0.169590	0.989032	0.236610	0.962375

B. Image Feature Selection

Selection of shape and texture extraction features is performed with independent t-Test involving a total of 200 datasets of both colon-polyp and colon-normal images. Statistically, the amount of data as much as 200 was considered sufficient for the implementation of independent t-Test [21]. Independent t-test results for extraction of shape and texture features, colon-polyp and colon-normal columns are presented in Table V.

TABLE V. IMAGE FEATURE SELECTION RESULT

Feature	Sig. (2-tailed)	Mean Difference
Roundness	0.000	7.97090
Aspect Ratio	0.000	-0.10728
Triangle	0.000	-0.15191
Contrast	0.397	-4.71329
Correlation	0.000	-0.01528
Energy	0.000	0.41566
Homogeneity	0.000	0.01298

Based on Table V, it can be seen that all extraction features of shape and texture features of colon-polyp and colon-normal images have values less than 0.05 except for the contrast feature. So it can be concluded that there are 6 selected features that will be Feedforward Neural Network inputs are roundness, aspect ratio, triangle, correlation, energy, and homogeneity.

C. Feedforward Neural Network

The Feedforward Neural Network experiment in this study was carried out in the Matlab IDE 2015R environment by six input features resulted from feature selection processes. In purpose of Feedforward Neural Network training, the dataset was automatically divided by default on Matlab 2015R into 70% sets for training, 15% sets for validation, and 15% sets for testing. To avoid the bias tendency in the sample pattern, Matlab random function (Matlab *dividerand*) was applied to distribute the dataset for training, validation, and testing. Parameter that used in training phase of Feedforward Neural Network include epoch = 15,000, performance function = mse, goal = 0.01, maximum fail = 6, minimum gradient = 1.00e-10, mu = 1.00+e10.

Sigmoid transfer function was used both in the hidden layer and output layer of Feedforward Neural Network. For simplification purpose, there only displayed training result for

Feedforward Neural Network architecture with selected input feature 6-(12)-2 architectures on Fig. 2 and training result for Feedforward Neural Network architecture with non-selected input feature 7-(12)-2 architectures on Fig. 4.

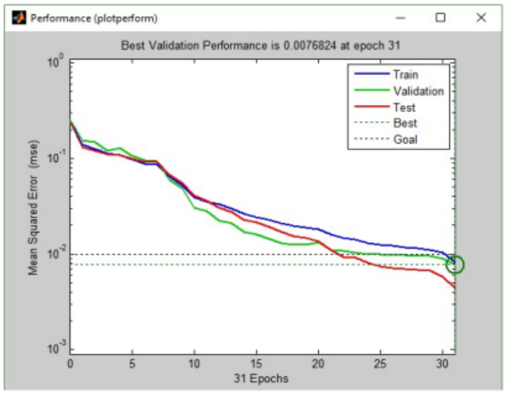

Fig. 4. Feedforward training result with selected image feature on 6-(12)-2 architecture

In other hands, Training result for Feedforward Neural Network architecture with non-selected input feature, on 6-(3)-2 architecture displayed on Fig. 5. From all image training result, it is concluded that in the training phase, there is no overtraining on all Feedforward Neural Network architecture [29]. So the results obtained can be compared each other and the training result can be accepted.

D. Evaluation of Result

Based on the training phase that has been implemented, then the value of accuracy and MSE of each architecture Feedforward Neural Network were obtained. The following results show the accuracy of polyp detection from the Feedforward Neural Network method with selected image features versus the Feedforward Neural Network with non-selected image feature. Comparison graph showed in Fig. 6.

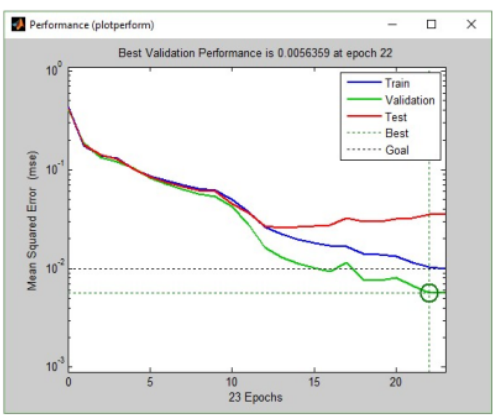

Fig. 5. Feedforward training result with non-selected image feature on 7-(12)-2 architecture

Based on Fig. 6, it can be concluded that Feedforward Neural Network with selected inputs can provide a higher accuracy value in recognizing polyps compared to Feedforward Neural Network non-selected inputs.

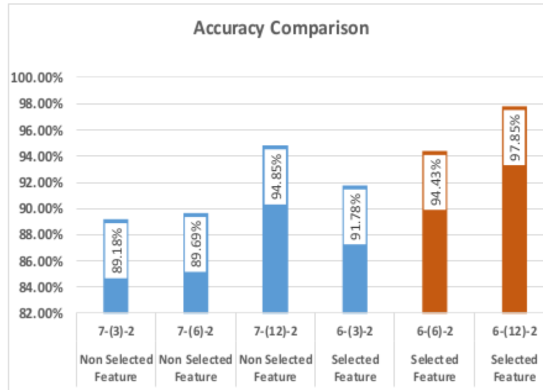

Fig. 6. Accuracy comparison between feedforward neural network with non selected image feature and selected feature on polyp detection

The highest recognition accuracy value is generated by Feedforward Neural Network with architecture 6- (12) -2 at 97.85%. On the other hand, the addition of the number of neurons in the hidden layer contributes to the optimization of Feedforward Neural Network to detect polyps, because Feedforward Neural Networks non-selected inputs and Feedforward Neural Networks with selected inputs get the best accuracy values on Neural Network architectures that have the largest number of hidden layer neurons.

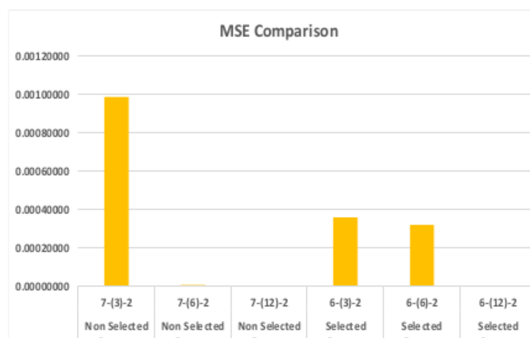

Fig. 7. MSE comparison between feedforward neural network with non-selected image feature and selected feature on polyp detection

Along with the accuracy, the mean squared error (MSE) values of each of the Feedforward Neural Network architectures are also influenced by the number of neurons in the hidden layer, as shown in Fig. 7.

From Fig. 7 it is seen that the Neural Network architecture with the number of hidden layer 6 and 12 neurons has a small MSE value compared to the Neural Network architecture which has 3 hidden layer neurons. The detail number of accuracy and

MSE comparison along each neural-network architecture showed in Table VI.

TABLE VI. ACCURACY AND MSE COMPARISON

Neural Network Architecture	Criterion	Accuracy	Mean-Squared Error (MSE)
7-(3)-2	Non Selected Feature	89.18%	0.00098600
7-(6)-2	Non Selected Feature	89.69%	0.00000536
7-(12)-2	Non Selected Feature	94.85%	0.00000320
6-(3)-2	Selected Feature	91.78%	0.00035800
6-(6)-2	Selected Feature	94.43%	0.00032000
6-(12)-2	Selected Feature	97.85%	0.00000012

IV. CONCLUSION

Feedforward Neural Network combined with selected image can be used as an effective tool for polyp detection that can help assist novice endoscopist educate themselves in recognizing polyps and supporting knowledge learned from knowledge that provided from experienced endoscopists. Based on experiments that have been implemented, the conclusion that the feature selection techniques greatly affect the accuracy of polyp detection with the highest accuracy of 97.85%. On the other hand, with the combination of transfer learning function, the hidden layer number, and training algorithms, the Feedforward Neural Network is able to provide high classification accuracy value, with low MSE level.

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