Human Intestinal Condition Identification Based-on Blended Spatial and Morphological Feature using Artificial Neural Network Classifier

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Abstract
Colon cancer is a type of disease that attacks the intestinal wall cell of humans. Colorectal endoscopic screening technique is a common step carried out by the health expert/gynecologist to determine the condition of the human intestine. Manual interpretation requires quite a long time to reach a result. Along with the development of increasingly advanced digital computing techniques, then some of the weaknesses of the manually endoscopic image interpretation analysis model can be corrected by automating the detection process of the presence or absence of cancerous cells in the gut. Identification of human intestinal conditions using an artificial neural network method with the blended input feature produces a higher accuracy value compared to the artificial neural network with the non-blended input feature. The difference in classifier performance produced between the two is quite significant, that is equal to 0.065 (6.5%) for accuracy; 0.074 (7.4%) for recall; 0.05 (5.0%) for precision; and 0.063 (6.3%) for f-measure.

Keywords: intestinal condition blended spatial morphological feature neural-networks classifier

I. Introduction
Colorectal cancer is a type of cancer that attacks the intestinal wall cell of humans. Wisconsin Reporting System (WRS), states that the type of colorectal cancer is the third highest cause of death after types of lung cancer and breast cancer, with a case of death of 9.5% of the total world population [1]. In Indonesia, colorectal cancer itself is ranked as the third cause of death after breast cancer and cervical cancer. Therefore, the abnormalities in the human intestinal wall need to be identified early to minimize the growth of cancerous cells that are more virulent, which can cause death. Health screening, such as endoscopy, is a simple step to detect abnormal growths in human intestinal cells wall [2][3]. Also, the process of early detection plays an essential role in health practitioners/gynecologists to determine the prognosis and type of treatment that patients must receive [4]. The right prognosis is accompanied by the right dosage of the drug to help speed the recovery of patients from colorectal cancer outbreaks.

Endoscopic screening technique is a common step carried out by the health experts/gynecologist to determine the condition of the human intestine by inserting a camera through the rectum to get an intestine picture [5]. The result of endoscopic screening is a digital image of the area around the intestinal wall [6]. During this time, the interpretation of endoscopic images is carried out manually or taken by the naked eye, thus requires quite a long time to interpret and produce results. This
manual interpretation is the cause of the long duration of time needed by the patient to find out the results of endoscopic screening [7]. This image interpretation has a weakness; it depends on the gynecologist’s expertise and experience [8]. Along with the development of increasingly advanced digital computing techniques, then some of the weaknesses of the manually endoscopic image interpretation analysis model mentioned previously can be corrected by automating the detection process of the presence or absence of cancer cells in the gut, by utilizing digital image processing techniques supported by the machine method learning. Automating the detection process can speeding up in production results and minimizing errors arising from the manual analysis model of endoscopic image interpretation.

II. Method

The identification of the intestinal condition to find cancerous colon condition in this study was divided into several steps presented in Fig. 1. The stages of Fig. 1 are explained in the following subsection points:

The first step, retrieving dataset is to get a colorectal endoscopic dataset. The colorectal endoscopy dataset consists of 200 image files generated from the colorectal endoscopic screening process with a .png format with VGA resolution (640 × 480 pixels). The images in the dataset are divided into two categories: (1) endoscopic images for normal intestinal wall conditions and (2) endoscopic images for abnormal intestinal wall conditions that are the origin of cancerous conditions. Examples images of normal intestinal wall conditions can be seen in Fig. 2.
While examples of endoscopic images for abnormal intestinal wall conditions can be seen in Fig. 3. The overall endoscopic dataset was obtained from the Internal Medicine Laboratory Dr. Sardjito Hospital, Yogyakarta-Indonesia, under supervision of Dr. Putut Bayupurnama Sp.PD.

The preprocessing aims out to ensure that the original image is ready for further processing at the feature extraction stage. Preprocessing also plays a vital role in avoiding bias in the output of a machine learning classifier. Preprocessing in this study is divided into several stages:

1. Convert Image RGB to Grayscale

At this stage, the conversion of RGB channel images into grayscale channels is carried out by using the formula presented in (1) by taking the red color conformity of 30%, green by 59%, and blue by 11% [2]. The RGB conversion extracts features of spatial images in the form of circularity, aspect ratio, triangularity, and cooccurrence matrix values.

\[
grayscale = 0.30 * r + 0.59 * g + 0.11 * b
\]  

where R indicates the value of the red channel, G the green channel, and B the Blue channel, an example of the results of converting an RGB image of endoscopic images under normal conditions to grayscale is presented in Fig. 4.

2. Image Resize

The image size reduction speeds up image processing and reduces the computational burden by change the pixel size of the original image from 640 × 480 pixels to 320 × 240 with the .png format [9].

3. Histogram Normalization

At this stage, the image histogram normalization is carried out which aims to equalize the brightness and contrast patterns that are owned by the image and the distribution of pixel intensities [10]. Histogram normalization is carried out using the formula presented in (2).
Equation (2) ensures that the interval of gray image values [0-255] is mapped in the range of values 0 until 1 only [11].

\[
l_{\text{new}} = \sum_{i=0}^{n} p(i)
\]  

(2)

where \( l_{\text{new}} \) is the value of pixel normalization mapping from a range [0-255] to range [0-1]; \( n \) is the number of pixels in an image \( I(x,y) \) with gray level degrees of \( (i) \); while \( p(i) \) represents the pixel probability in gray level degrees of \( (i) \).

Feature extraction from endoscopic images is carried out to retrieve relevant information from each image so it can be used as input to the machine learning classifier. In this study, relevant information extracted from endoscopic imagery includes morphological information and spatial information. Morphological information, taken based on the size of circularity that is the result of the division between the pixel area value and the pixel perimeter on the region of interest (ROI). The circularity formula is presented in (3) [6].

\[
4\pi \times \frac{\text{area}}{\text{perimeter}}
\]  

(3)

Whereas spatial feature information, extracted based on the co-occurrence matrix, which will produce information includes:

1. Energy
   
   Energy is a measure of pixel conformity in an image. Energy reflects the degree of texture smoothness of an image. The lower the energy value, the rougher the surface texture of the image and vice versa [12]. The calculation of the energy value is presented in (4)
   
   \[
   \text{energy} = \sum_{i,j} P(i,j)^2
   \]  

(4)

2. Contrast
   
   Contrast value is the simple comparison between foreground objects and image background. Contrast is a unit of local image variation values [12][13]. The calculation of the contrast value is presented in (5)
   
   \[
   \text{contrast} = \sum_{i,j} |i - j|^2 P(i,j)^2
   \]  

(5)

3. Correlation
   
   Correlation is a gray-level linearity value of two or more adjacent pixels in an image [14]. The calculation of the correlation value is presented in (6)
   
   \[
   \text{correlation} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p_{ij}}{\sigma_i\sigma_j}
   \]  

(6)

4. Homogeneity
   
   It is a value of the distance between elements in the co-occurrence matrix in gray images [11]. The calculation of the homogeneity value is presented in (7)
   
   \[
   \text{homogeneity} = \sum_{i,j} \frac{p_{ij}}{1+|i-j|}
   \]  

(7)

where \( P(i,j) \) is the elements of the co-occurrence matrix; \( \mu_i \) and \( \mu_j \) express the mean value and \( \sigma_i \) and \( \sigma_j \) reflect the standard deviation in row \( i \) and column \( j \) in.

The machine learning model built in this study is an artificial neural network that utilizes the backpropagation function. The architecture of artificial neural networks is presented in Table 1. At the input layer of the artificial neural network architecture, 4 neurons and 5 neurons are used following the number of feature extractions from the colonic endoscopy image. While the hidden layer / intermediate layer uses 9 and 11 neurons following the equation stated by [12][15] that the use of a hidden layer of \( 2n+1 \) (where \( n \) is the number of input neurons) can accelerate the training process and the generalization results of neural networks. At the output layer, the binary-shot coding concept is used where 1 represents the condition of the cancerous image, while 0 represents the normal image condition [16].
Validation of the classification results is Accuracy, Recall, Precision, and F-Measure. The three parameters are obtained from true positive (TP), true negative (TN), false positive (FP), and false-negative (FN) metrics [17].

1. TP is a condition when the input “A” identified by machine learning matches the ground truth “A”.
2. TN is a condition when the “non-A” input identified by machine learning matches the “non-A” groundtruth.
3. FP is a condition when input “A” is identified by machine learning as a “non-A” groundtruth.
4. FN is a condition when the input “non-A” is identified by machine learning as the “A” groundtruth.

From the indicators mentioned above, an equation can be formed, stating the accuracy presented in (8) until (11) [18].

\[
\text{accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (8)
\]
\[
\text{recall} = \frac{(TP)}{(TP+FN)} \quad (9)
\]
\[
\text{precision} = \frac{(TP)}{(TP+FP)} \quad (10)
\]
\[
\text{f – measure} = \frac{2 \times \text{Recall} \times \text{Precision}}{(\text{Recall}+\text{Precision})} \quad (11)
\]

### III. Results and Discussions

The Matlab 2015\textsuperscript{8} programming platform that runs on the Windows 10 64bit operating system was used as the experimental base for this research. Endoscopic images used in this study have a total of 200 images with two categories: 100 endoscopic images of cancer category and 100 endoscopic images of the normal category. The dataset is divided into three parts to avoid bias on the results of artificial neural network training. The first part is the training dataset (70\%), the second part is the testing dataset (15\%), and the third part is the validation dataset (15\%). The default function Matlab 2015R (dividerand) is used as a dataset divider.

Feature extraction produces two kinds of features: morphological and spatial features. Morphological features produce information on circularity values. On the other hand, spatial features product information on energy values, contrast, correlation, and homogeneity. The values of spatial and morphological features are used as input from the artificial neural network classifier. Some morphological and spatial extraction values are presented in Table 2.

Although there are many algorithm choices available in the artificial neural network training process [19][20], this research uses Quasi-Newtonian (matlab: trainlm) algorithm because the Quasi-Newtonian algorithm can produce an optimal artificial neural network learning process and faster to achieve generalization of output values compared to training algorithms such as Scaled-Conjugate or Resilient-Propagation [21]. The parameters of the artificial neural network (ANN) training process are presented in Table 3.

Training and testing are carried out in the Matlab R2016a environment that runs on an operating system platform on Windows 10 (64-bit) with an Intel® Core i5® 4310 processor computer; 8 GB Memory; Intel HD VGA Card. For simplification purpose, there will be presented only the results of
Table 2. Spatial and morphological feature extraction result

| Image Condition | Energy   | Contrast | Correlation | Homogeneity | Circularity |
|-----------------|----------|----------|-------------|-------------|-------------|
| Normal Image-1  | 0.18948  | 0.96020  | 0.20885     | 0.93779     | 0.95982     |
| Normal Image-2  | 0.18523  | 0.96077  | 0.17188     | 0.93618     | 0.93752     |
| Normal Image-3  | 0.19485  | 0.97017  | 0.21369     | 0.94112     | 0.85313     |
| Normal Image-4  | 0.20669  | 0.95677  | 0.17129     | 0.93349     | 0.77344     |
| Normal Image-5  | 0.16762  | 0.96966  | 0.17314     | 0.94374     | 0.90534     |
| Polyp Image-1   | 0.29893  | 0.94862  | 0.15432     | 0.91132     | 0.73008     |
| Polyp Image-2   | 0.20979  | 0.96249  | 0.21411     | 0.94192     | 0.91683     |
| Polyp Image-3   | 0.26171  | 0.96698  | 0.15399     | 0.92710     | 0.79852     |
| Polyp Image-4   | 0.24069  | 0.95111  | 0.18719     | 0.92481     | 0.66581     |
| Polyp Image-5   | 0.29893  | 0.94862  | 0.15432     | 0.91132     | 0.82152     |

Table 3. ANN training set parameters

| No  | Parameter              | Value                      |
|-----|------------------------|----------------------------|
| 1.  | Epoch                  | 25,000                     |
| 2.  | Performance Function   | mse (mean squared error)   |
| 3.  | Goal                   | 0.01                       |
| 4.  | Max. Fail              | 6 (Matlab default)         |
| 5.  | Min. Gradient          | 1.00e-07                   |
| 6.  | µ                       | 1.00e-10                   |

the artificial neural network training process with 5-(11)-2 architecture with blended input feature (spatial and morphological) are presented in Fig. 5.

From Fig. 6 it can be seen that the training process does not experience overfitting conditions. The absence of overfitting is indicated by the blue line = train; green = validation; red = test that decreases simultaneously and does not intersect each other. A summary of the metrics for the results of artificial neural network training is presented in Table 4. A summary of the confusion matrix of the artificial neural network classifier for blended (spatial and morphological) input features is presented in Table 5. The summary of the confusion matrix of the artificial neural network classifier for the non-blended (spatial only) input feature is presented in Table 6.

The artificial neural network training process with a blended (spatial and morphological) input feature produces a regression value of 0.97232 presented in Fig. 6. Otherwise, the artificial neural network training process with a non-blended (spatial only) input feature produces 0.89151 regression value.

![Performance](image_url)

Fig. 5. Artificial neural network training result for blended feature.
Based on Table 5 and Table 6, it can be evaluated the performance of artificial neural network classifiers with blended and non-blended input features with indicators of accuracy, recall, precision, and f-measure. The values of the performance indicators artificial neural network classifiers with blended input feature, derived from Table 5 and Table 6 are presented in Table 7. For ease of use, a comparison from Table 7 also presented on Fig. 7.
IV. Conclusion

Identification of human intestinal conditions using an artificial neural network method with the blended input feature produces a higher accuracy value compared to the artificial neural network with the non-blended input feature. The difference in classifier performance produced between the two is quite significant, that is equal to 0.065 (6.5%) for accuracy; 0.074 (7.4%) for recall; 0.050 (5.0%) for precision; and 0.063 (6.3%) for f-measure. So it can be concluded that the use of blended features as neural network inputs sufficiently influences the results of identification of the condition of the human intestine.

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Declarations

Author contribution
All authors contributed equally as the main contributor of this paper. All authors read and approved the final paper.

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