Skin Cancer Clasification Using Region Growing & Recurrent Neural Network

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***Abstract*—Skin cancer is a disease caused by mutations in the skin of cells. Melanoma and non-melanoma skin cancers are the two basic classifications for skin cancer. In addition, it is estimated that 5.9-7.8% of all cancer cases each year involve skin cancer. In Indonesia, 65.5% of skin cancers are basal cell carcinomas, followed by 23.0% squamous cell carcinomas and 7.9% malignant melanomas. When not discovered early, melanoma skin cancer can result in a high fatality rate. Basal cell carcinoma and squamous cell carcinoma are two examples of nonmelanoma skin cancers (NMSCs), which are far more frequent but far less likely to spread and cause mortality. Diagnosis made by an expert or doctor takes a long time and is often inconsistent because the environment and personal conditions influence the expert's condition. To minimize this problem, this research aims to introduce image processing methods for early skin cancer detection, the Region growing method, and artificial neural networks RNN for classification. It is hoped that this method of early cancer detection can be done quickly and does not require much money. This study will use two methods to detect skin cancer: the Region growing method and RNN-LSTM. This research aims to introduce the Region of interest (ROI) method and artificial neural networks to detect skin cancer.**

Keywords—Cancer skin, Region of Interest, Region Growing, Recurrent Neural Network, LSTM

I. INTRODUCTION

Skin cancer is a skin disease caused by damaged skin cells and changing normal cells to become malignant. Damaged skin cells do cell division continuously to become uncontrolled and abnormal because of DNA damage. Although skin cancer can be seen with the naked eye. A fast and accurate diagnosis requires a dermatologist with deep knowledge of skin cancer and its treatment [1]. Meanwhile, [2]recommends self-examination every six months and annual dermatologist visits to mitigate the potential for skin cancer.

Excessive UV rays from the sun can cause skin cancer types cutaneous malignant melanoma (CMM), squamous cell carcinoma (SCC), and basal cell carcinoma (BCC) [3]. It was reported by [4] that skin cancer ranks third in Indonesia after uterine and breast cancer. Furthermore, it is said that skin cancer is found in 5.9-7.8% of all types of cancer per year. The most common skin cancer in Indonesia is BCC (65.5%), followed by SCC (23%), CMM (7.9%), and other skin cancers. The type of skin cancer most at risk, melanoma, has a high mortality rate, especially if not detected early. Nonmelanoma skin cancers (NMSCs), such as basal and squamous cell carcinoma, are more common but less metastatic, and only a minority lead to death.

In the last 1-decade, image processing snowballing, and there have been several studies on the application of image processing and computer vision to detect cancer cells. Among them, there are researchs; in [5] this research, the researcher uses the Region Growing method to detect skin lesions (skin wounds). This study found that the application of the growing image processing region can help doctors detect skin lesion diseases with a high degree of accuracy—95%. The research [6], Uses RNN for the classification of Skin Cancer and gets high accuracy – 93%, also the research , use region growing and RNN GRU to classification of Skin Cancer and get high accuracy – 91% [7]

Based on these studies and problem cases of skin cancer in Indonesia, this research intends to introduce image processing methods for early skin cancer detection using the split and merge segmentation method and Region growing. It is hoped that with these methods, early cancer detection can be done quickly and does not require much money.

This research will use two methods for detecting skin cancer: the region-growing method and the RNN-LSTM classification algorithm. The accuracy and performance of the Region growing Segmentation and Recurrent Neural Network LSTM for skin cancer detection will be evaluated.

II. RELATED WORK

In this research detecting skin cancer disease from dermoscopy image will be done with Region-Growing and RNN method.

These RNN methods are usually used for text processing but in this part some research that have been done implementing combine Region Growing segmentation and RNN in image processing field are reviewed and to reaching more understanding about Region Growing segmentation and RNN algorithm.

The application of the Region Growing segmentation method for breast cancer was tested in a paper [8] and obtained the results. The study using the Region Growing method and the results of the 90% accuracy. Researchers recommend optimizing the threshold in the region-growing implementation and employing other algorithms.

In research [5], using the Region Growing method to detect skin diseases, researchers used 3 methods for preprocessing data before segmenting it with region-growing. From the results of this study, it was found that the grayscale image preprocessing method combined with the growing region obtained a high level of accuracy for the detection of skin lesions, which was 95%. Suggestions from researchers to use the same technique to be applied to other skin diseases.

In research [6] to detect skin cancer, researchers used the RNN artificial intelligence method for classification and K-mean cultering for segmentation. In this study, a high accuracy rate of 93% was obtained. The researcher's suggestion from this research is to use other techniques in segmenting or classifying.

In research[7] to classification skin cancer, researchers used Region Growing and RNN GRU method for classification. In this study, a high accuracy rate of 91% was obtained. even though the dataset the researcher use is very simple, only 200 image for training and test. The researcher's suggestion from this research is to use other techniques in for classification for comfrim or improved classification accuracy.

III. RESEARCH METHODOLOGY

A. Segmentation

The primary purpose of image segmentation is to extract various picture features. These extracted image features can be merged or split to create objects of interest. The built objects can be further studied and comprehended. Image segmentation refers to the process of splitting an image into groups of pixels that are homogeneous according to some criteria. The result of segmentation is the separation of a picture into interconnected regions. The purpose of segmentation is to divide a picture into relevant parts. Thresholding, region-growing, statistical models, active contour models, and clustering have all been used to segment medical images because of their complex intensity distribution. Generally, segmentation is performed on the basis of two fundamental properties: discontinuities and similarities. "Discontinuities" is an approach for dividing a picture based on sudden shifts in grayscale levels. The primary techniques include the identification of isolated points, lines, and edges in an image, as well as the estimation of the image's edge using edge detection. Similarities are based on thresholding, region growing, and region splitting and merging; it's region-based segmentation.

B. Region Growing Segmentation

Based on [9], Region growing starts from an incomplete initial segmentation and tries to merge unlabelled pixels into one of the initial regions, usually called the seed area. Whether a pixel should join a region is based on several fitness functions that reveal the similarity between the Region and the candidate pixels.

As proposed in [10], the order of processing pixels is determined by a global priority queue which sorts all candidate pixels based on their fitness values. Image segmentation algorithms assign pixels into homogeneous regions, for example, which can be classified with higher accuracy than can be obtained by classifying individual pixels.

C. Artificial Neural Network (ANN)

The human nervous system was the main motivation for the development of the ANN computing system, which is essentially based on the enormous interconnectivity and parallel processing architecture of the human nervous system. An ANN model is a data-driven mathematical model that uses machine-learning neurons to solve issues. ANN may discover complex nonlinear input-output relationships without direct input knowledge or physical process. [11].

The typical architecture of an ANN consists of an input layer, a hidden layer, and an output layer. There are one or more hidden layers in between the input and output layers that connect them based on weight matrices, bias, or a variety of activation functions. The input and output layers are independent of one another. Figure 1 illustrates a typical ANN structure. [12]

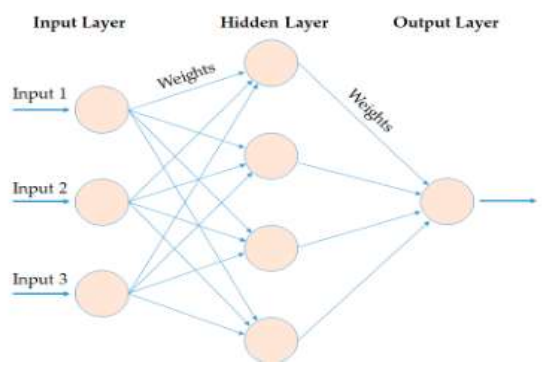

Figure 1 ANN Architecture [10]

D. Recurrent Neural Network (RNN)

RNNs are a type of artificial neural network in which connections between nodes in each layer of a directed graph with succeeding variables are formed.

The RNN structure is made up of an input layer, one or more hidden layers, and an output layer. RNN has a structure similar to a chain of repeating modules. The module is used as a memory to store vital data from the prior phase of the procedure. In addition, RNNs have feedback that permits the neural network to receive input sequences. Therefore, the result of step t-1 will be relayed back into the network to impact the results of step t and each subsequent step.

An input unit, an output unit, and a hidden unit that repeats itself and will evolve into a whole network are depicted in Figure 2, which may be considered as a clear explanation of how the RNN algorithm operates. The value of Xt serves as the input for the time step t, while the value ht represents the output of the time step to t. [10]

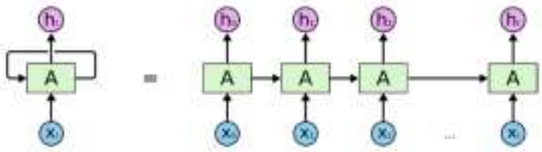

Figure 2 Sequential processing in RNN [13]

The efficiency of the RNN method that can handle the Vanishing Gradient Problem on Vanilla RNN can be improved using different versions of RNN, such as GRU (Gated Recurrent Units) and LSTM (Long Short-Term Memory Network), which are both examples of RNN variations.

E. Vanishing Gradient Problem

Because *RNN* work is based on an intense time (t), the data processed in the previous intense time will affect processed data at the next intense. Cost function and weight (w) are calculated and adjusted every time. If data move from t-1 to t, data need to be multiplied by W, and data will continue to perform the process if owned data sequence is very long. The value of W is very small, and the value range is between 0.1 – 0.001. if there are many process multiplication by W, then the gradient's value will get smaller. The smaller gradient, the more challenging to reach cost function. This problem is called Vanishing Gradient Problem. The smaller gradient will impact how significantly the model is created. Then the model will not be able to re-learn. To solve these problems, we will use RNN-LSTM that can store long-term memory processes [14]

F. Long Short-Term Memory (LSTM) Neural Network

Long Short-Term Memory (LSTM), one of the evolution RNNs, was developed as a solution to the shortcomings of the RNN that were discussed before. The solution was to increase the number of module interactions (or cell). LSTM RNN can learn long-term dependencies and store data for extended time periods. [12]. A chain structure is used to model and organize LSTM RNN. Rather than using a single neural network like RNN, LSTM has four layers that interact and talk to each other in different ways. In Figure 3, we can see how an LSTM RNN is constructed..

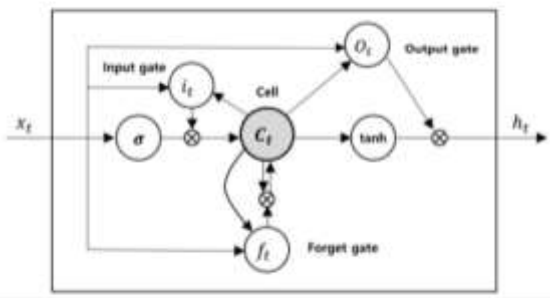

Figure 3 Gate units of Long short-term memory (LSTM)

As shown in fig 2.3, there are three gates in an LSTM system: an input gate, a forget gate, and an output gate. Computation's process on lstm carry out with these steps [15]:

- Input gate: choose the value to be updated
- Forget gate: decides what information will be removed from the C_{t-1} context
- Output gate: decide how the result is found.

All gates employ sigmoidal non-linearity, and the state unit could act as an input for other gating units. in the eq. (12) that is sigmoid activation function used at forget gate:

$$ft = \sigma(Wf.\,[ht-1, xt] + bf) \quad (12)$$

Next gate is input gate, in this gate there are two process that must be done, the first process is make selection of value which will be renewed with sigmoid activation function and the second step is calculate function tanh that will create new vector value and save the value at memory cell. Below is the eq. (13) and eq. (14) used in input gate:

$$it = \sigma(Wi.\,[ht-1, xt] + bi) \quad (13)$$

$$\hat{c}t = tanh(Wc.\,[ht-1, xt] + bc) \quad (14)$$

Then, there is cell gate that will do replacing process for memory cell value before the process to the new value that calculated from combining the value in forget gate and input
gate with the following eq. (15):

$$ct = ft * ct-1 + it * \hat{c}t \quad (15)$$

Last gate is output gate, this gate will be doing selection of memory cell value that will be selected as output value with the calculation of sigmoid activation function, then that value from sigmoid activation function is multiply by tanh activation function which has selected memory cell value as input, the it will produce the output value. Below is the eq. (16) and eq. (17) used at output gate:

$$ot = \sigma(Wo.\,[ht-1, xt] + bo) \quad (16)$$

$$ht = ot \tanh(ct) \quad (17)$$

IV. Results and Discussion

A. Research Material

The research material used in this study is a public dataset, namely Skin Cancer: Malignant vs. Benign is a .jpg image type data obtained from the Kaggle website; this data size is 171.61 MB and has two directories in it, which have separate images between Benign and malignant skin cancer. Figure 2 depicts some example images that were used in this research.

Figure 4. Sample image of the dermoscopy data set

B. Algorithm Flow

In this research, *Region Growing* will generate Regions of Interest, and RNN will be used for classification. The chart of the stages passed in this research can be seen in Figure 3, and There are five steps in this research:

- Pre-processing
- Segmentation
- Feature Extraction
- Classification
- Evaluation

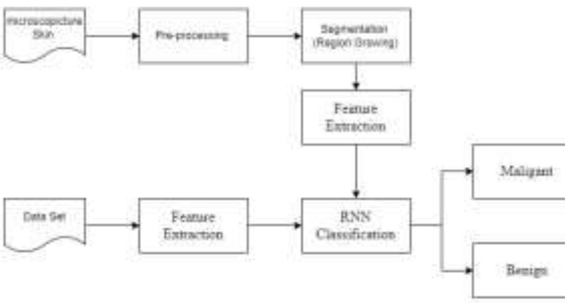

Figure 5. Research Stages

First, pre-processing from the skin cancer image data, convert the RGB image into a Grayscale image. Then, resize is done so all images processed in same size. After that, Hair or bubble removal, furthermore, Contrast enhancement using the Adaptive Histogram equalization Method from the.[16]

The primary objectives of pre-processing are to increase image quality, minimize extraneous noise, and accentuate the image's small features.

The second step, generate a *Region of Interest* based on *Region Growing* method.

The third step. Feature Extraction using the GLCM Gray level co-occurrence matrix is a statistical technique for analyzing the spatial connection between pixels. Each pixel inside a picture has its own intensity. Five critical elements are identified for implementations in the this paper: Energy, entropy, contrast, correlation, and homogeneity (a certain shade of gray);

The fourth step performs a classification-based model already trained from the dataset Using RNN-LSTM

The fifth step is to calculate an accuracy test on the detection results.

C. Method Evaluation

The analysis of the segmentation results for Region growing and RNN classification methods will be tested by calculating the Precision and Recall of the image results. For calculation precision and recall, equations (1) and (2) need to be used

$$\text{Precision} = \frac{TP}{TP+FP} \ldots\ldots(1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \ \ldots\ldots\ldots(2)$$

Precision is the number of regions that match the predictions from the image that match or match the Ground Truth database, while recall is the number of regions that appear that match the predictions that match.

Relative value between Precision and Recall, in our study, we use the value of = 0.5 as introduced by [17], [18].

D. Experiment Result

This research will combine two methods, The Region Growing for segmentation and RNN LSTM for Classification. Since this research is still in progress, the latest result of the Experiment is from training the RRN model with 80% training data and 20% validation data with 128x128 resized image. he Fig. 9 is the summary of the model used for this experimentation, first is input layer of 128x128 image then LSTM layer with 128 nodes, then dense
layer with 128 nodes, dropout layer with 0.2 rate and output layer with 4 nodes. The data is set to be trained for 100 epochs
but in case the model is overfitting so early stopping method
is implemented, the model stopped at epoch 66, the model is

trained for 8 minutes and 3 seconds in total execution time
and resulting with 0.5740 for loss, 0.7150 for accuracy, 0.5807 for validation loss, and 0.7235 for validation accuracy. The detail off all iteration accuracy can be seen at
Fig. 10, for the iteration loss detail can be seen at Fig. 11, the
blue line is the training accuracy and the orange line is validation accuracy.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 128)               131584

 dense (Dense)               (None, 128)               16512

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 4)                 516
```

Fig. 6. RNN Model Summary

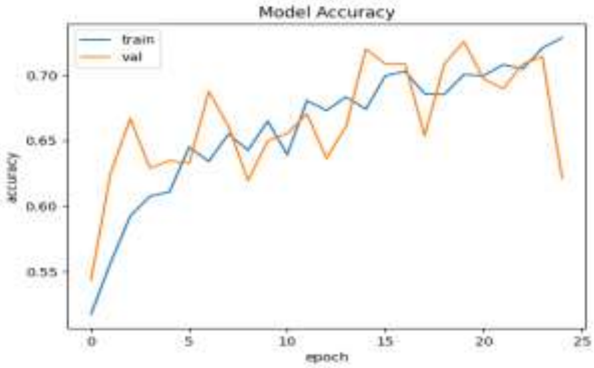

Fig. 7. RNN Model Accuracy

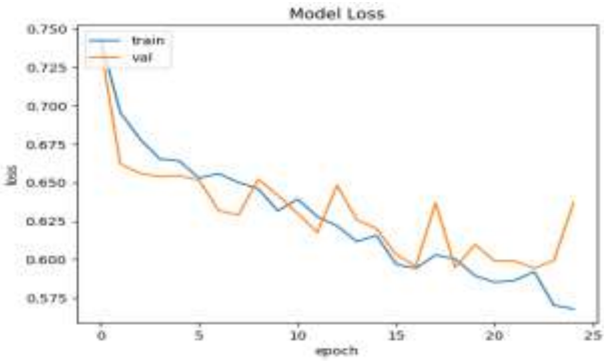

Fig. 8. RNN Model Loss

V. CONCLUSION

By looking at the advantages and disadvantages of previous research, choosing the Region Growing method for the Region of Interest segmentation of skin cancer and RNN LSTM for classification are expected to be the right choice. the latest result of the Experiment is from training the RRN model resulting with 0.5740 for loss, 0.7150 for accuracy, 0.5807 for validation loss, and 0.8003 for validation accuracy. Since this research is still on progress , the accuration rate may be can improved by combining with segmented image that have focused interest area and change data train based feature extration image. For future research, the dataset can be preprocessed further such as controlling the brightness and splitting the training and test data with different partition, then for the Region Growing method can be combined with algorithm for automatic seed also for the RNN model can be tested for prediction to show the model performance in detecting skin disease and increasing the epochs to see better accuracy.

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