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Combination of Active Contour and CNN-based Segmentation Methods to Improve Accuracy in Detecting Rice Diseases

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Abstract

Rice diseases are one of the main factors causing decreased productivity and threatening national food security. The main problem in controlling rice diseases is the delay and inaccuracy of symptom identification in the field. This study aims to develop an artificial intelligence-based rice disease detection system through a combination of Active Contour and Convolutional Neural Network (CNN) methods. The research object is rice leaf images taken from rice fields in Pulau Sejuk Village, Batubara Medan, with a dataset of 600 images consisting of healthy leaves and 3 types of rice diseases. The Active Contour method is used in the segmentation stage to extract leaf areas precisely, while CNN is applied for the disease classification process. The results show that this combination of methods can significantly improve the accuracy of rice disease detection. The developed system is expected to assist farmers and stakeholders in the early detection of rice diseases, thereby supporting food innovation and increasing sustainable agricultural productivity.

Keywords: Segmentation, Active Contour, CNN, Detection, Rice Disease

1. Introduction

Rice is a major food commodity in Indonesia and many agricultural countries, so the sustainability of rice production significantly impacts national food security. However, rice productivity is still often disrupted by various plant diseases such as leaf blast, brown spot, and bacterial leaf blight, which can significantly reduce yields if not detected early [1]. Conventional rice disease identification still relies on visual observation by farmers or agricultural extension workers, which tends to be subjective, time-consuming, and prone to diagnostic errors [2].

Developments in artificial intelligence, particularly computer vision, have opened up new opportunities for leaf-image-based plant disease detection. Deep learning methods such as convolutional neural networks (CNNs) have been shown to be capable of classifying plant diseases with high accuracy [3,4]. However, CNN performance is heavily influenced by the quality of the input image, particularly during the leaf segmentation stage. Inaccurate segmentation can cause the model to have difficulty distinguishing between leaf and background areas, thus reducing classification accuracy [5].

The segmentation used in this study utilizes the Active Contour segmentation method, which is a model that places the initial contours at the beginning. Local intensity information is very useful in handling inhomogeneities and noise intensity, but is very sensitive to the initial contour initialization [6]. The Active Contour segmentation approach involves separating the desired region from an image using energy values. A contour is a line that defines the desired image region, and a contour refers to a group of interpolated points. Several contouring techniques involving external and internal forces are used to calculate the curvature of the model. While curves are always related to an energy function, the desired contour in an image is determined by subtracting the energy function with the aim of precisely segmenting the desired object region [7].

Previous research by [8] demonstrated robust image segmentation using the Active Contour model (ACM), which has weaknesses such as sensitivity to low contrast, high intensity inhomogeneities, and image noise. In comparison, the GSLCE model proposed in this study demonstrated superior visual image segmentation results with an accuracy of 93.73%, higher than ACM, which only achieved 76.07% accuracy, and required significantly less processing time. Previous research by [9] applied the Active Contour method to improve the quality of B-mode (ultrasonic) images, increasing the target's lateral resolution by 67.9% to 81.2%.

Furthermore, previous research by [10] developed the SLIF model for vector-valued (color) image segmentation. This study successfully addressed data loss due to image dimensionality reduction and poor segmentation due to image intensity inhomogeneity.

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The SLIF model achieved 94% accuracy, significantly better than other segmentation methods.

Meanwhile, in the research on Convolutional Neural Networks (CNN) by taking the object of keratitis disease, namely by [11]. Where using the method of Deep Learning, namely Convolutional Neural Networks (CNN) for automatic diagnosis of infectious keratitis with the aim of highlighting the area of infection. Infectious keratitis is a group of corneal disorders in which the corneal tissue experiences inflammation and damage caused by pathogen infection. Among them, Fungal Keratitis (FK) and Acanthamoeba Keratitis (AK). In Vivo Confocal Microscopy (IVCM) thus enabling imaging of various layers of the cornea, providing an important picture for early and more accurate diagnosis. data on IVCM-Keratitis consisting of a total of 4001 samples of AK and FK images, as well as Non-Specific Keratitis (NSK) classes and healthy corneas. based on CNN for automatic diagnosis of infectious keratitis. Densenet161 performed best with accuracy, precision, recall, and F1 scores of 93.55%, 92.52%, 94.77%, and 96.93%, respectively. The results demonstrate the potential of Deep Learning-based models for early and automatic diagnosis of AK, with the highest accuracy.

From the review of previous studies above, an effective segmentation approach is the Active Contour method, which can adaptively adjust contours to follow object boundaries based on image shape and intensity information and based on the object and background regions in an image, thus distinguishing or separating detected objects. This method is widely used in medical image processing and is beginning to be applied to plant images to extract leaf regions more precisely [12]. Therefore, combining Active Contour-based segmentation with CNN is expected to improve the quality of extracted features and improve the accuracy of rice disease detection.

Although various studies have successfully applied Convolutional Neural Networks (CNNs) to detect plant diseases with high accuracy, most of these studies still rely on simple preprocessing and segmentation, or even use images without optimal segmentation [1], [3]. On the other hand, studies utilizing advanced segmentation methods such as Active Contour are generally limited to the object extraction stage without direct integration with CNN models, and are rarely applied specifically to rice disease cases [12]. Furthermore, few studies have systematically evaluated the impact of combining Active Contour and CNN-based segmentation on improving rice disease detection accuracy. Thus, there is a research gap in developing an integrated approach that combines Active Contour and CNN to produce more precise segmentation and significantly improve rice disease classification performance.

This research aims to develop a leaf image-based rice disease detection system by combining the Active Contour method in the segmentation stage and CNN in the classification stage. The contribution of this research is expected to improve the accuracy of rice disease detection and support faster and more accurate decision-making in disease control efforts, thereby contributing to increased productivity and innovation in the agricultural sector.

2. Methods

2.1. Segmentation

Segmentation is a process that performs image processing which aims to separate certain objects from the background or other objects [13]. Image segmentation is one of the fields in Computer Vision which discusses how computers learn and recognize segments of an image according to the specified labels. In reality, many data have unbalanced classes or labels, which will certainly affect the level of accuracy of a prediction. The main goal of segmentation is to obtain certain information contained in an object [14]. So segmentation is an image processing to obtain the desired object provisions [15].

2.2. Active Contour

The Active Contour method is an approach to object segmentation that uses a closed curve that can widen or narrow based on the energy value of an image [16]. An initial curve is placed outside the object to be segmented, then through an iterative process, the curve moves closer to the object's boundary until it finally finds the object's boundary [17]. Active Contour also uses mathematical descriptions to identify objects within an image. In Active Contour, the contour length is considered in terms of the contour energy. As the contour approaches the object's boundary, its length typically decreases because the method attempts to minimize the contour energy by aligning it with external factors such as brightness or color, among others [18].

The desired image contour is determined by subtracting the energy function. The curve's energy function is the sum of the external and internal energies combined and can be written as:

$$E_{snake}=\int_0^1 E_{internal}\,((s))+E_{image}(v(s))+E_{con}(v(s)))ds \quad ....(1)$$

Active Contour is an energy minimization process. Therefore, the set of x and y coordinates of the curve in an iteration has a smaller energy than the previous iteration while satisfying the three existing energies, namely Eint, Eimg, and Econ [19]. Because the aim is to find the minimum energy from the equation above and look for a set of x and y coordinates of the Active Contour curve that fulfills it.

2.3. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of deep learning model capable of processing data in the form of grid patterns [20]. Convolutional Neural Networks (CNN) are specifically designed to process multidimensional data such as images and videos. Therefore, CNN is able to automatically extract important features from input data through multi-layer convolutional layers. In general, CNN architecture consists of several main types of layers, namely convolutional layers, pooling layers, flattening layers, and fully connected layers.

3. Results and Discussions

The results and discussion at this stage will explain the implementation that has been implemented or created using the active contour method for segmentation and classification using CNN, resulting in the detection of rice diseases. This includes presenting prediction results, accuracy values, summaries, symptoms, actions to be taken by farmers, and future notes for farmers regarding treatment and maintenance during the rice growing period.

This research was conducted in rice fields in Pulau Sejuk Village, Lima Puluh District, Batu Bara Regency, Medan. The data used were 600 images of rice leaves. The types of diseases detected were categorized into three categories: eaf blast, brown spot, and bacterial leaf blight, with a healthy category. These three disease categories were the most common among rice leaves in the village fields. Therefore, the researchers implemented an application that had been created and designed using the active contour segmentation algorithm and CNN classification using Python programming, and an Android UI interface. The aim is to make it easier for farmers or users to directly use the application to detect and identify rice diseases.

3.1. Data Set

The data used in this study consisted of 600 images of rice leaves. The disease types to be detected were divided into three categories: eaf blast, brown spot, and bacterial leaf blight, as well as a healthy category. The sample data presented by the researchers can be seen in Figure 1 below:

Data Set Padi Desa Pulau Sejuk

Figure 1. Sample Rice Data from Pulau Sejuk Village

In Figure 1. Above is the data of Rice Leaves located on land in Pulau Keren village with a total of 600 images, while the sample displayed is 12 images. The rice leaf image data is used for detection and further review as test material in research to obtain detection that has an accurate percentage of object detection provisions and provides important information and information for farmers.

3.2 Hasil Implementasi

Based on the results of this study, which have been well-implemented and can be easily used by farmers to detect rice diseases, the results obtained from this study can be seen in Figure 2.

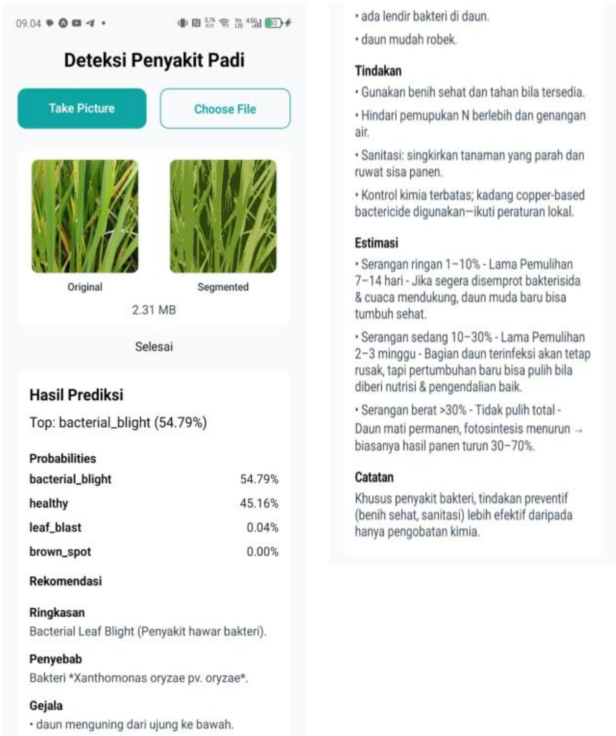

Figure 2. Results of rice disease detection with bacterial leaf blight type

Figure 2 above shows the results of a study that directly captured images of rice leaves from farmers using a user interface. The results clearly demonstrate an accurate detection rate of 54.79%, with a percentage of disease-affected rice plants, including leaf blast (0.04%) and brown spot (0.00%). The percentage of rice leaf health was 45.16%.

The detection results are clearly visible, and the information provided is very helpful and facilitates farmers' actions, understanding the symptoms, causes, and estimated treatment options. The detection results, which fall into the Healthy Rice Leaf category, are shown in Figure 3 below.

Figure 3. Results of Rice Disease Detection with Healthy Types

Based on the detection results carried out in Figure 3 above, it shows a Healthy percentage of 73.24% and also identified one disease at 26.75%, namely bacterial leaf blight. The results of the research conducted can find results that greatly support village farmers in identifying the health and types of rice diseases and can take appropriate and quick action in handling them to minimize damage and losses. Behind that, the results obtained also provide great ease of use of the application.

4. Conclusions

The research results obtained from the detection of 600 data sets resulted in 586 images being detected precisely and accurately, with a percentage of 97.6%. Meanwhile, 0.6% of the images were undetectable due to blurry and unclear objects and backgrounds during image capture in rice fields. These images comprised 4 images.

The detection results in this study can prove and assist farmers in categorizing their rice leaves and also improve their technological understanding of their agricultural land.

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Author Contributions Statement

Contributor Role Taxonomy (CRediT) to recognize individual author contributions, the contributions made can be seen in the following table.

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