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Classification of Dragon Fruit Stem Diseases Using Convolutional Neural Network

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Abstract— A holticulture plant known as dragon fruit (pitaya) is a fruit that has many benefits and is widely cultivated by farmers in several areas of Banyuwangi. In dragon fruit plants there are various kinds of diseases that attack including red spot, stem rot, black rot, scab, and mosaic. Farmers still recognize diseases on dragon fruit stems manually so that sometimes there are errors in disease recognition. In this research, a system was developed to identify the types of diseases on dragon fruit stems. This system was built by proposing the Convolutional neural network method with the proposed architecture using the Python programming language with the Tensorflow, Keras, and Scikit-Learn libraries. The proposed system is tested using k-fold cross validation with tunning parameters fold = 5 and epoch = 5. The training results show that the highest accuracy performance value is 85.06% with the data used as test data as many as 191 images producing 147 correct data and 44 data wrong, while the average overall accuracy score was 76.43%.
Keywords— Pitaya Disease Detection; Disease Classification; Deep Learning; Multi-Layer Percepteron; Digital Image Processing

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I. INTRODUCTION

A holticulture plant known as dragon fruit (Pitaya) has many advantages for human health. The antioxidant components (phenols, flavonoids, vitamin C, and betacyanin), vitamin B3 (niacin), fiber, MUFA (monounsaturated fatty acid), and PUFA (polyunsaturated fatty acid) found in dragon fruit work to prevent the body from reducing its cholesteral blood levels [1]. Additionally, anthocyanin chemicals found in the skin of those fruits play a role in diabetes, cancer, and heart disease prevention. Anthocyanin are also valuable in cosmetics, pharmaceuticals, and other industries [1]. The major reason Indonesians favor dragon fruit is due to its high amount of nutrients.

Dragon fruit plants are widely cultivated by farmers in several areas in Banyuwangi. These are Pesanggaran, Bangorejo, Siliragung, Tegaldlimo, Purwoharjo, Sempu, Cluring and Gambiran areas which are centers for the cultivation of this type of plant. Most of the vacant land is planted with dragon fruit. This can be seen from the data compiled by the official website of the Banyuwangi Regency Government. In 2019, dragon fruit became a commodity in the fruit category that was most widely cultivated in Banyuwangi after Siamese Oranges, Bananas and Mangoes [2]. The increase in yields from year to year does not necessarily cause dragon fruit farmers in Banyuwangi to experience success in their cultivation. Farmer's always face a variety of problems, especially related to disease attacks on stems and fruits. In a study conducted by Arif Wibowo, it was stated that there are several diseases that attack dragon fruit stems. These diseases include anthracnose, brown spots, red spots, stem rot, black rot, mosaic, root ulcers, and scabies [3], [4]. Until now, farmers have not been able to identify with certainty the disease in dragon fruit plants and have not found the right solution to overcome this problem.

Today the world is in an all-digital era where the use of massive information technology is carried out in various fields, especially those related to artificial intelligence technology and computer vision. The use of computer vision for object classification or detection has been tested out by several researchers, such as for the classification of emotions [5], [6], batik classification [7], [8], as well as classifications related to plant diseases such as in the image of apple leaves [9], potato leaves [10], rice leaves [11], sugarcane leaves [12], [13], mango plants [14], and detection of other plant diseases [15], [16]. Research that examines the classification or detection of dragon fruit was carried out in some previous study. In previous studies, segmentation techniques were developed to take objects affected by disease and classify the three diseases on dragon fruit stems [17]–[19]. In our previous research, only classifying three types of diseases on dragon fruit, such as red spot, scabies and insect stings with an optimal accuracy of 85% and also with the limited datasets. Other researchers developed a detection model to sort out diseased and non-diseased

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diseases in dragon fruit [20]. In this study applied and compared two classification methods, namely the Neural Network and Random Forest methods with the prediction accuracy in the range of 70% to 82.9% for both classifiers. However, this study classified only four classes in which the two classifiers were used in two comparison experiments, namely healthy and diseased fruits and leaves.

Another study conducted disease image segmentation on dragon fruit using the Fuzzy C-Means Clustering (FCM) and Two-Dimensional Otsu thresholding algorithms [21]. In this study, segmentation was carried out on four types of diseases on dragon fruit, namely stem rot, mosaic disease, ulcers, round spot chlorosis. An expansion of previous research is presented in which the number of classified diseases is added to five types of diseases in this study. In addition, the dataset used is also increasing. Consequently, this study should lead to a more accurate and powerful model. The Neuronal Convolutional Network (CNN) method using two convolution processes with different matrix numbers was proposed in this study. The first convolution uses 32 filters with a 3x3 matrix of kernels and the second convolution stage uses 64 filters with a 2x2 matrix of kernels which is followed by flatten, namely changing the output of the convolution process in the form of a matrix into a vector which will then be forwarded to the classification process using Multi-Layer Percepteron (MLP). The use of CNN in model development is because this method is a powerful method in classifying images with a large number of datasets and class labels [22]. The hypothesis of this study is that the proposed method can better classify disease data on dragon strain imagery.

II. RESEARCH METHOD

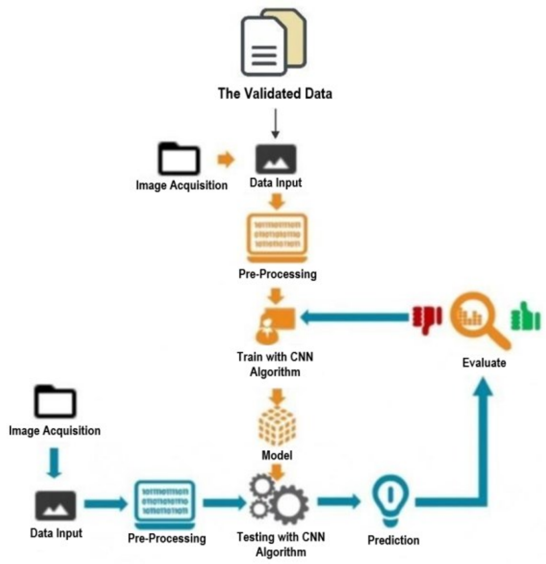

Fig 1. Design System

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The proposed research method used Convolutional Neural Network with data-adapted architectures for classifying some dragon fruit diseases. The overall methodology includes some phases, such as Image acquisition and data input, pre-processing, train and testing with CNN method, and evaluate, as shown in the figure 1.

A. Image Acquisition and Data Input

At this stage, data collection is carried out on the type of disease on the stems of dragon fruit plants as much as possible. This data collection process requires image data in jpg/jpeg format with clear and unblurry images, the same shooting distance, and different camera angles. Image acquisition is divided into 10% for test data, 10% for data validation, and 80% for training data from the total of all data. In this study, there are 5 types of desired diseases, namely Red Spot (A), Stem rot (B), Black Rot (C), Scabies (D), and Mosaic (E) as shown in Figure 2. Based on the dataset obtained, it has been validated by experts in the field of pest and plant disease control, so that the validated data is processed at a later stage.

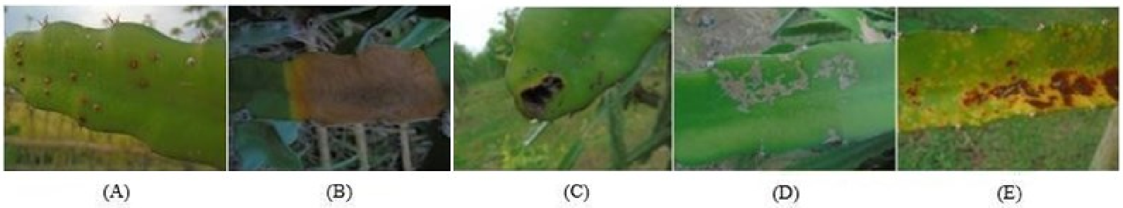

Fig 2. Image Acquisition and The Dataset Types

B. Pre-Processing

The pre-processing stage, often referred to as data augmentation, is the stage of preparation before the image is further processed. A variety of methods are used in data augmentation to create a "new" training sample from the original by introducing random perturbations and perturbations, while also guaranteeing that the data class labels remain constant. By altering the image pixels (goal size) in this stage's Keras Image Data Generator, it is possible to make the next procedure go more quickly. After that, perform a horizontal flip, shear range, and zoom range. Please see the following sections for more information:

1. The target size is the image size used in the formation process which, by default (in pixels), is 256px×256px. The dimensions of all specified images will be adjusted to this resolution,
2. The shear range consists of angulating the image. This process is different from rotation because in rotation the image is rotated, but in cropping it defines an axis and stretches the image to some angle. These are called shear angles. This is a form of stretching that does not occur in rotation. The value of the shear range shall be a float representing the

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anti-clockwise shear angle in degrees. The shift of image A to image B as far as m in the x direction and n in the y direction, is formulated based on the following equation:

$$B[x][y] = A[x + m][y + n] \quad (1)$$

3. Zoom Range is a process for magnifying and de-magnetizing images. It takes a float value between 0.0 and 1.0. then zoom in or demagnify the imae randomly by taking the upper value as 1 + zoom_range and the lower value as 1 - zoom_range. The image zoom process is performed through equation 2, where sx and sy are the scaling factors of each in the x and y direction:

$$x' = sx\,.\,x\; y' = sy\,.\,y \quad (2)$$

4. Flip horizontally when the default value is incorrect. If we set the horizontal value as true, the image will be rotated horizontally to the left and to the right. The equation for reflection on the Y (Cartesian) axis from image A to image B is:

$$B[x][y] = A[N - x][y] \quad (3)$$

After carrying out the pre-processing process like the steps above, the results obtained can be shown in the following figure:

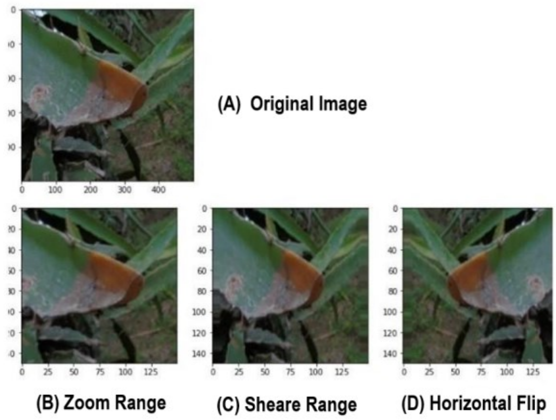

Fig 1. The Example Result of Pre-Processing phase

C. Train and Testing with Convolutional Neural Network (CNN) Method

The Convolutional Neural Network (CNN) approach, which classifies input images into distinct categories based on their output values, is used to classify images after they have successfully completed the pre-processing stage. The CNN method is used to process the training and testing data. The CNN approach will provide the most accurate model for categorizing the various diseases on dragon fruit stems during the data training phase. The data testing procedure will use this model as its foundation in addition to additional test data.

As a general rule, the CNN method consists of two steps: feature learning and classification. Feature learning is a technique that allows a system to run automatically to determine the representation of an image into features in the form of numbers that represent the image. The classification step is a step in which the characteristics learning outcomes will be used for the

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classification process based on predetermined sub-classes. The input image for the CNN model uses a 64x63x3 image. The number three is an image that has 3 channels namely red, green and blue values (RGB). At the feature learning step, the input image is subsequently processed using convolution and pooling. The suggested design features two convolution layers and two convolution processes. Each convolution uses a distinct kernel size and number of filters before flattening the result. This procedure, also known as the fully connected layer stage, converts the feature map that results from the pooling layer into a vector form. The first convolution uses 32 filters and kernels with a 3x3 matrix. Then the pooling process is carried out using a 2x2 size by shifting the mask by two steps. In the second convolution stage using a total of 64 filters and kernels with a 2x2 matrix and followed by flatten, namely changing the output of the convolution process in the form of a matrix into a vector which will then be forwarded to the classification process using Multi-layer Percepteron (MLP) with the number of neurons in defined hidden layer. Each image dataset is then ranked according to the value of the neurons in the hidden layer using the soft-max activation feature. Architecture improvisation and selection based on research that has been done before and other literature sources that produce optimal performance [8], [22]–[25]. The following is the architectural design of the CNN method proposed in this study:

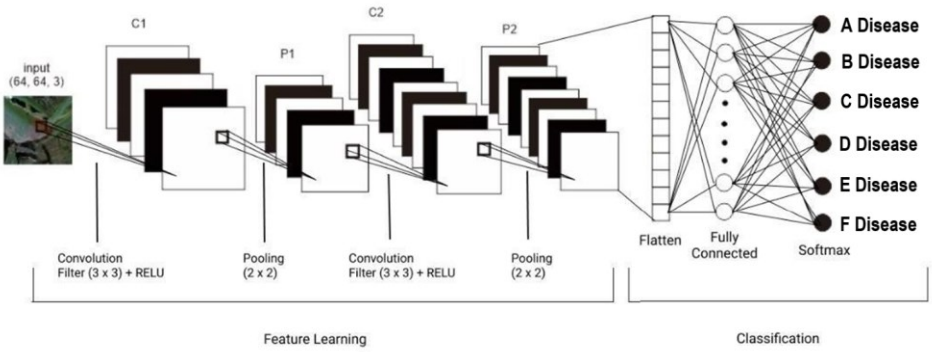

Fig 4. The Proposed of CNN Architecture

D. Output (Model)

The results of this training process can be referred to as a model and stored in a file with the extension *.h5 where this file will later be used for the classification (matching) process to identify the types of diseases on dragon fruit stems.

E. Evaluate

This step consists of assessing and analyzing the results of data processing with the proposed method. When evaluating the performance of the proposed methodology, use the Confusion Board approach. The confounding matrix represents the forecasts and actual conditions of the data generated by the machine learning algorithms. The performance system is measured in accordance with the precision parameter. Accuracy is the relation between the exact forecasts

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(positive and negative) and the data set. The confusion matrix with 4 different value combinations can be written based on the following equation:

$$\text{Accuracy} = {TP + TN}/_{TP + FP + FN + TN} \qquad (4)$$

TP (True Positive) is positive data that is predicted to be true, TN (True Negative) is negative data that is predicted to be incorrect, FP (False Positive) is negative data but is predicted as positive data, and FN (False Negative) is positive data but is predicted as negative data. Accuracy describes how accurately the model classifies correctly.

III. RESULT AND DISCUSSION

The initial stage of the training process involves the collection of datasets. All image data collected are equal in size: 5152px x 3864px. The image data was captured using a Canon PowerShot SX430 IS digital SLR camera. The process of collecting the data was completed during the day. The dataset collected was validated by experts in the field of pests and plants from the University of Jambi and divided into 5 classes namely Red Spot, Stem Rot, Black Rot, Scabies, and Mosaic.

The initial step in the data set processing process is to acquire images. Image acquisition is very important when at this point the data needs to be entered into the training data repository. Each training data class is broken down according to the file for each class. In the data directory, there are 5 folders that will be read in this process including red spot disease, stem rot, black rot, scabies, and mosaic where each folder contains images according to its class. The five folders are then put into the train folder. Apart from these folders, there are also test and validation folders where these two folders are taken from the validated dataset. Then 20% of the training data is divided and put into the test folder. The list of directories from the original folder should be entered into the sourceFiles list variable as the first step in reading the data. Next, use the conditioning command to see if the folder has any data. Calculating the total amount of data to be split is the next step if there is data in the directory. The sum of all the data in sourceFiles times all the data that must be retrieved in percent is the total data. After that, the data will be stored in the transferFileNumbers variable and retrieve data randomly with the amount of data according to the transferFileNumbers variable and move the image data according to the index from the origin folder to the destination folder. However, if there is no data in the source folder it will display the message "No file moved, Source empty!". So that the system can read all the folders that have been defined, a loop is needed to read files or folders. After reading the folder, the

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images are read in list form so that the images are queued one by one until all images use the syntax in the os library, namely os.listdir.

A. The Result of Pre-Processing Stage

The next step is to construct a data generator variable with the name datagen while still utilizing the ImageDataGenerator package from Keras. This data generator's purpose is to produce picture data from an existing file or folder. Rescale the data in this generator to 1/255, set the shear and zoom ranges to 0, and perform a horizontal flip. This stage's goal is to generalize the input data so that it can be processed correctly when using CNN to train and test data. The following step is to design a flow that specifies the data source. In this study, the set folder that has been established is reached utilizing flow from the directory where the function directs. The outcomes from the pre-processing stage are displayed follows:

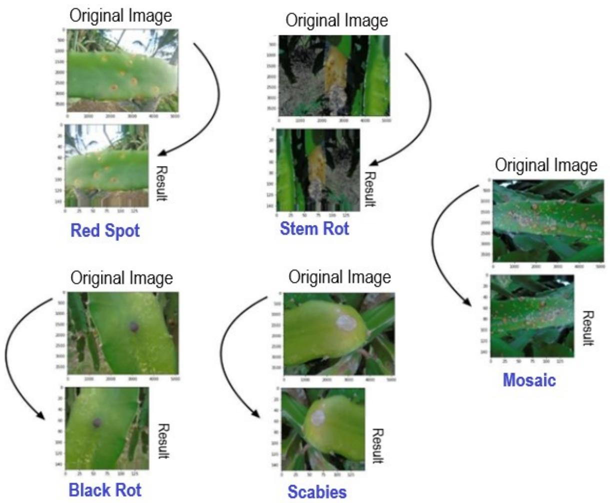

Fig 2. The Pre-processing Results

B. The Classification Results with The Proposed CNN Method

The classification procedure, which is the following step, is carried out using the CNN algorithm and the suggested architecture from the techniques section. Finding the K value from the K-fold cross validation, the epoch value, and the learning rate is the first stage in the classification process. The parameters used in this investigation were K = 5, epoch = 5, and learning rate = 0.01. Using data for training and data for validation, the algorithm model is developed. The CNN network's organizational structure must be established before moving into the training phase. The model training stage, which uses the Scikit-Learn library's Stratified K-Fold validation, comes next. The X and Y variables, which already have filename and label data from the train folder, are used as parameters to be split using k-fold. Then the file names and labels that have been issued based on the index are moved from the train folder to the validation folder. The figure 5 shows the image processing process until it is classified through the CNN network.

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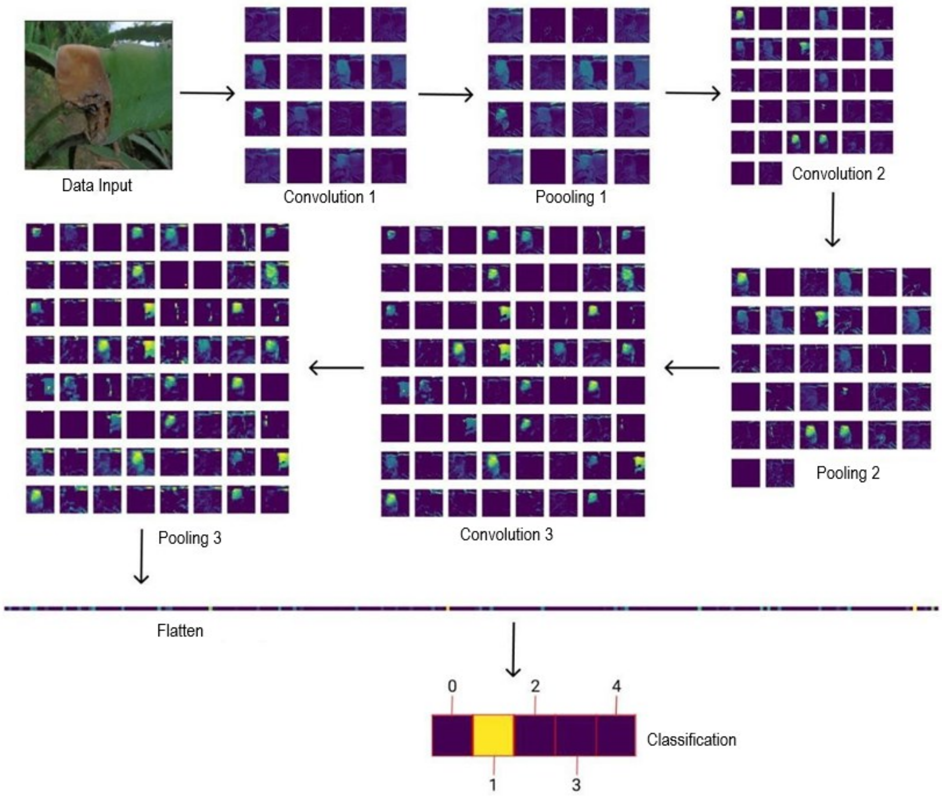

Fig 3. The Result of Classification Process

Taking the output of each activation layer from CNN using the keras library. Based on figure 5, the dataset was successfully classified at index 1 of 5 outputs. The 5 outputs are the sum of the disease categories trained and according to the "classLabels" variable, the 1st index of the variable is stem rot. Of course, the best parameter values are also required in order to produce the best model. These variables include the number of epochs, the size and number of filters for each layer. Epoch is the period of time after the complete dataset has undergone the Neural Network's training process before starting over for one round. Because one Epoch is too big to be fed into the computer in one go (feeding), it must be split up into smaller batches. [22], [26], [27]. It is acknowledged that running the entire dataset through the neural network once is insufficient for one epoch and that running the full dataset through the neural network numerous times is required. However, keep in mind that Gradient Descent is an iterative technique that must be used with a limited dataset in order to optimize learning, therefore updating weights with just one epoch is insufficient. [22], [26], [27]. Because the appropriate epoch value cannot be known, in this study a parameter tuning of 5 epochs was carried out. Figure 6 shows the results of CNN classification using 5 folds and 5 epochs for each fold with 16 filters in the first convolution, 32 filters in the second convolution, and 64 filters in the third convolution. The kernel size used is 3x3 pixels, and uses max pooling with pool_size 2x2.

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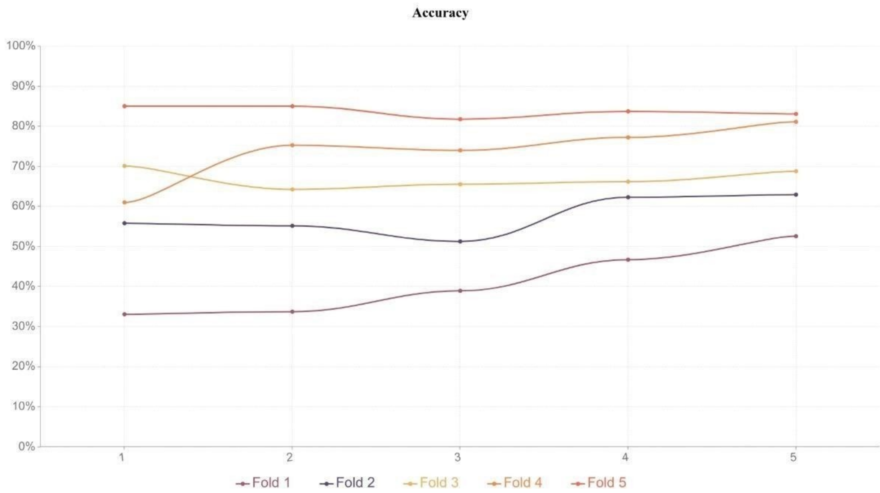

Fig 4. The Accuracy of training result with k-fold cross validation

```
Found 191 images belonging to 5 classes.
191/191 [==============================] - 134s 705ms/step

Hasil Sebenarnya Data Test
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 4 4
 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4
 4 4 4 4 4 4]

Hasil Prediksi Data Test
[0 0 0 4 4 4 0 0 1 0 0 0 0 4 0 4 0 0 0 4 0 0 4 4 0 0 0 0 0 0 0 4 0 2 0 3 0
 0 0 4 3 0 0 4 4 0 0 0 0 1 1 1 1 4 1 1 1 1 1 4 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 4 1 1 1 0 2 2 0 2 3 3 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 4
 3 3 3 3 1 3 3 3 3 1 3 3 3 3 3 0 4 3 3 3 3 3 3 3 4 3 3 4 1 4 4 4 4 4 4 4 0
 4 4 1 4 0 4 4 4 4 4 4 4 4 4 1 1 4 4 4 3 4 4 4 4 4 4 0 4 0 4 4 4 0 0 0 4 4
 4 0 4 4 4 4]

Accuracy  : 0.7643979057591623
```

Fig 5. Classification Result of Data Testing

You can observe each fold's accuracy in figure 7 above. We can observe that the epoch and fold values used to calculate the accuracy fluctuations are fixed. The second epoch and fifth fold yielded the accuracy score of 85.06%, which was the best performance outcome among all experiments. The first epoch and first fold display the lowest accuracy, with a percentage value of 33.12%. Additionally, in the second trial, we manually divided the training halves into 80%:20%. During the second experiment's training and testing phases, 191 data were employed. Based on Figure 8, the classification results had the highest accuracy value of 0.7643 (76.43%) utilizing Scikit-Learn's accuracy score. For more detailed classification results can be seen in the following table 1 (confusion matrix table) and figure 9.

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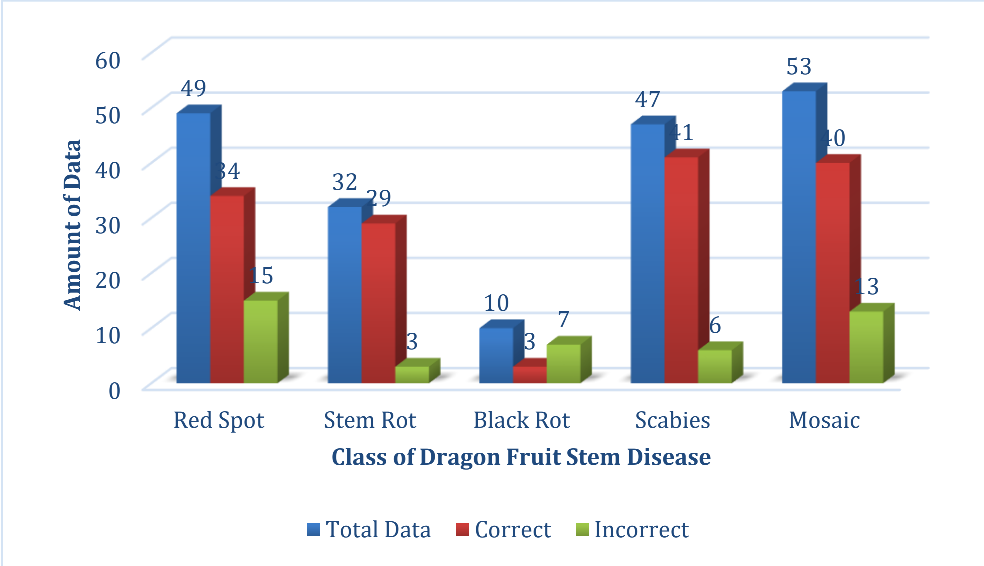

Fig 6. Correct percentage of classification results in per category

Table 1. Classification Results Based on confusion matrix table

The Factual Data	Amount	The Prediction Result				
		Red Spot	Stem Rot	Black Rot	Scabies	Mosaic
Red Spot	49	34	1	1	1	12
Stem Rot	32	0	29	0	0	3
Black Rot	10	3	1	3	3	0
Scabies	47	1	2	0	41	3
Mosaic	53	8	4	0	1	40

The table shows that the red spot and mosaic classes are where inaccurate data detection is most often. Red spot-labeled data revealed a mosaic of 12 photos. Eight mosaic-designated images were found to be red blotches in the meanwhile. This demonstrates that the feature contours of the illness patterns in the red spot and mosaic datasets are nearly identical, indicating the need to review and amass more information on these two diseases. The information gathered can more accurately depict each illness on dragon fruit stems. Figure 8 displays the accuracy number that was acquired for each type of sickness; this accuracy value was manually calculated using the formula (True/Amount) x 100. It is evident from the trials that the accuracy value for each class label. Red Spots are accurate in this illness type by 69.38%. Stem rot illness has a 90.62% accuracy rate, Black Rot has a 30% rate, Scabies has an 87.23% rate, and Mosaic has a 75.47% rate. As for the comparison from previous studies, research on identifying the types of diseases on dragon fruit stems using the Color Moments and Gray Level Co-Occurrence Matrix method which has been carried out by previous studies can detect types of disease on dragon fruit stems with an accuracy value of 87.5% [17], [18].

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IV. CONCLUSION

Based on the experiments, it can be concluded that the collection or dataset collection obtained a total of 961 images consisting of 5 disease categories, namely red spot disease, stem rot, black rot, scabies and mosaic. The image used has a size of 5152px x 3864px which is subsequently processed using the proposed method. The proposed method uses the CNN method to categorize diseases on dragon fruit stems by dividing 80% as training data and 20% as testing data. The training process uses an image measuring 150px x 150px so that from the input image with a large resolution, then the resizing stage is carried out using the shear range approach at the pre-processing stage In addition, the zoom and horizontal toggle phases are also carried out at the preprocessing stage. Based on system performance validation of the model created using k-fold cross validation with 5 folds and 5 epochs, the greatest accuracy value was 85.06%, and the average accuracy was 76.43%. Based on the research that has been done, it has been discovered that accuracy has not yet achieved optimal accuracy values, so in future research it will be necessary to improve the proposed CNN architecture in addition to the number of datasets used so that later it is anticipated to get an optimal model with more datasets and classes/labels.

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