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Classification of Tomato Plants Diseases Using Convolutional Neural Network

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***Abstract*— Tomato plants are many cultivated by farmers to get their fruit. Several obstacles in the cultivation process result in the process of producing products that require maximization. Constraints faced by farmers are diseases that attack plants. Farmers in dealing with the disease simply recognize the disease with their naked eyes and take action without knowing how to deal with it. Several approaches have been made in the recognition process that can be handled by using deep learning. The results shown using this process produce a good performance. Therefore, this paper has the aim of making and evaluating recognition of the diseases in plants seen on tomato leaves automatically using a deep learning approach. Convolutional Neural Network (CNN) is one of the deep learning methods used in handling object recognition processes. Recognition process tomato plants disease used a data set consisting of 6 different types of disease. Recognition process used 100 image data for each type of disease as training data, while as many as 60 image data are used as testing. This study used three different types of data sets that are used differently, consisting of original image RGB, blending images, and a mixture of RGB images and blending images. The classification results using a mixture of RGB images and blending images have a better performance than others by producing a Genuine Acceptance Rate (GAR) of 96.7% following by the percentage of False Acceptance Rate (FAR) values of 3.3% and False Rejection Rate (FRR) of 3.3%.**

***Keywords*— tomato diseases; deep learning; convolutional neural network; diseases recognition.**

I. INTRODUCTION

Tomato plants (*Lycopersicum Esculentum*) are one of the categories of horticultural plants that are included in the *Solanaceae andisone* family. Many of these tomato plants are grown by farmers because they are needed in daily life to be consumed in fresh or processed forms [1]. Tomato is one of the vegetable plants which has a nutrient content which can grow in subtropical, tropical, and temperate regions [2]. One of the potential horticulture plants and has a promising market prospect. Tomato plants are widely used as food and beverage production materials so that they are needed for relatively many needs. The attack of diseases and pests makes the process of growth of tomatoes disturbed so that the prices obtained are greatly increased due to the lack of supply [3]. Attacks of bacteria, fungi, and viruses can cause tomato plant diseases. The process of spreading tomato plants is needed. This is very important in increasing the yield of the production of tomato plants. Previously, the process of recognizing disease was still done manually. With this, the recognition process is even said to be less efficient. On the other hand, with this process, the process of introducing the disease can occur until the process of overcoming it.

Problems recognizing diseases that are carried out automatically can be the foundation in this study. The existence of Artificial Intelligence in the use of technology is very broad applied in computer science research and the field of operational research that is needed in making the process of recognition carried out automatically [4]. One application of Artificial Intelligence for the recognition process is the use of machine learning. The branch of machine learning is deep learning, which is introduced with the application of deep network, used datasets complex, high-level abstract, and heterogeneous that focus on processing image and audio [5]. Deep learning is part of computer vision that aims at processing image classification, video classification, and automatic speech recognition [5], [6]. Convolutional Neural Network (CNN) is a deep learning algorithm that is popular in image processing with networks better known as topology and commonly used in performing object recognition in images [7]. CNN consists of deep networks with several types of layers, such as convolution layer, pooling layer, and fully connected layer, so that from the process of all these layers to produce a form of regularization [8].

In this work, classification of tomato disease features that used on shape, color, and texture. The method offered in this classification study uses an in-depth learning approach to Convolutional Neural Network (CNN). Classification is carried out automatically using input data in the form of RGB images and blending images. Blending images are carried out between original images in the form of RGB in combination with canny filters, to produce images with sharpened textures that they have without removing the color they have on tomato leaves. The data set used in this paper consists of original data set with color space RGB, blending images data set, and mixture blending images with RGB images data set.

II. Materials and Method

Artificial Intelligence is now almost applied in all aspects of daily life, as mentioned in artificial intelligence, where it can gather knowledge and knowledge reasons to solve complex problems [4]. Machine learning is part of Artificial Intelligence that is currently popular to do the development process and implement this technology. In general, the concept of machine learning is where the learning process is carried out by the machine to determine the pattern in the data where later the pattern is used for the prediction process. In addition to machine learning, this chapter also discusses the in-depth learning approach, which is the basis for developing research in this paper. In this section, we describe these studies have relevance about machine learning, deep learning, and its application in image classification.

Research Fuzzy and Neural Network-based Tomato Plant Disease Classification using Natural Outdoor Image. The classification process consists of three types, i.e., a fuzzy inference system based on subtractive, adaptive neuro-fuzzy, and multi-layer feedforward back backpropagation. Process classification used consisted of data of five types of tomato plant diseases and a healthy tomato plant. The dataset has 180 images used for training and testing in this classification. Results about this classification accuracy are the best yield with a multilayer feedforward backpropagation classifier of 87.2% [9].

Classification of tomato disease using image processing where main identified used four types of tomato diseases by conducting image segmentation and SVM-Multiclass algorithm. The classification process uses training data with 80 images of one type of disease, so that the whole training process to detect four major diseases with 320 images. Determine the classification in this study using SVM-Multiclass algorithm by using data sets that have been finished out by the previous segmentation process. The remaining images are used for the testing process and 15% of the sample samples are used as model validation [10].

Detection and classification of plant diseases consists of four main phases, there are first phases k-means clustering technique, phase 2 to masking the green pixels and the pixels on the boundaries, phase 3 features extraction implemented by Color Co-occurrence Method (CCM) and phase 4 is detection of leaves diseases using Neural Network. Process Neural Network made training and validation process, that process important to make an accurate model NN. Process classification used 5 types of various diseases plant and a healthy leaf plant. This classification used RGB images data set. Result this classification using Neural Network classifier achieved precision between 83% and able to active 94% [11].

Identification plants diseases can be used as a defense mechanism against the diseases. Process identification use Convolutional Neural Network (CNN) which consists of different layers which are used for prediction. The database is used from crowd AI with ten different leaf diseases such as apple black spot, apple broad leaf spot, apple needle leaf spot, apple normal, bell paper normal. Blueberry normal, cherry normal, cherry powder normal, corn blight, and corn rust. The results proposed system is based on python and gives an accuracy of around 78% [12].

Mango leaf diseases identification using Convolutional Neural Network (CNN) used to improve the quality and quantity of crop yield. Identification mango leaf disease in mango plant species. Process identification uses five different leaf diseases such as *anthracnose*, *alternaria* leaf spots, leaf *gall*, leaf *webber*, leaf burn a dataset consisting of 1200 images of diseased and healthy mango leaves. The images are resized from normal size in dataset 4608 x 3456 to 256 x 256. The results this paper proposed CNN model archives an accuracy of 96,67% for identifying the leas diseases [13].

A. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a development of Multilayer Perceptron (MLP) designed to process two-dimensional data. CNN is also part of Deep Learning because this algorithm has a high network depth and is widely applied image data. A CNN focuses on a process that contains data in the form of images that focus on building a network that is most accurate in accordance with the needs in obtaining information from the process that is executed [14]. Data entered the CNN network can be in the form of raw pixel images or in the form of transformations, the network will then highlight certain aspects of the image [9]. The layer parameter consists of a set of learn able filters (or kernels) that have a small receptive field but are extended through the full depth of the input volume. During the advanced feed, each filter convoluted across the width and height of the input volume calculates the product point and produces a 2-dimensional activation map of the filter [15]. As a result, the network learns about filters to produce a training model that is used for the introduction process. CNN layers can be said to consist of 3 types: convolutional layer, pooling layer, and fully connected layers [16].

B. CNN Architecture

Workflow CNN Architecture differs from the traditional multilayer perceptron (MLP) to some degree of shift and invariant distortion. This research proposed the classification of tomato diseases using Convolutional Neural Network (CNN) model architecture with seven stages layers, five convolutional layers, and two fully connected layers. Every convolutional layer we used max-pooling the highest pixel value in a 2 x 2 patches translated in increments of 2 pixels. The convolutional layer is the block building of a CNN. In that layer has parameters of the leaner consist of filters that extend through the full depth of the input.

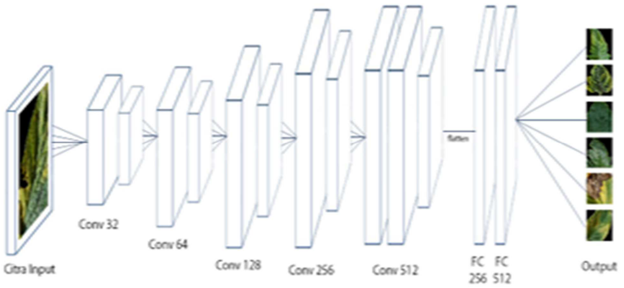


Fig. 1 The CNN Architecture

The convolution layer places in the input images through a set of convolutional operations each of which activates certain features from the input images [17]. Each convolutional layer defines input representation according to the level of abstraction. Fully connected layer has functions to map the activation volume from the combination of previous different layers into a class probability distribution [18].

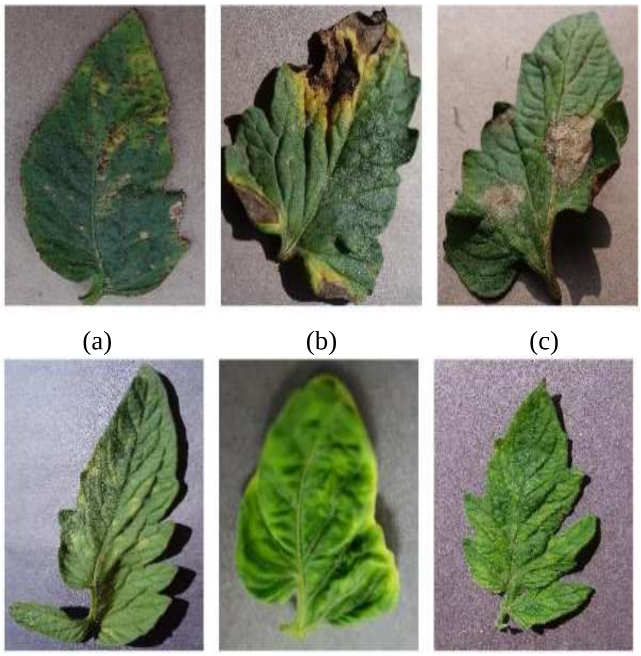
TABLE I
CNN ARCHITECTURE

LAYERS	Size	Output Size
INPUT	160 X 160	-
CONVOLUTION + RELU	32 (3x3) filters	(158,158,32)
MAX POOLING	(2x2) filters	(79,79,32)
CONVOLUTION + RELU	64 (3x3) filters	(77,77,64)
MAX POOLING	(2x2) filters	(38,38,64)
CONVOLUTION + RELU	128 (3x3) filters	(36,36,128)
MAX POOLING	(2x2) filters	(18,18,128)
CONVOLUTION + RELU	256 (3x3) filters	(16,16,256)
MAX POOLING	(2x2) filters	(8,8,256)
CONVOLUTION + RELU	512 (3x3) filters	(6,6,512)
CONVOLUTION + RELU	512 (3x3) filters	(4,4,512)
MAX POOLING	(2x2) filters	(2,2,512)
FULLY CONNECTED + RELU + DROPOUT	20% dropout	256
FULLY CONNECTED + RELU + DROPOUT	20% dropout	512
SOFTMAX	6 way	6 way

Fig. 1 is the CNN architectural model used in the process of classification tomato plants diseases. The CNN process consists of feature extraction process and classification process Feature extraction is described by convolutional layer and pooling layer consisting of 5 block layers. The flatten process occurs to get the fully connected value from the results of the convolutional layer. The fully connected process is known as the classification process. The features received from flatten will be used for the classification process. Table 1 shows a detailed of the CNN architecture shown in Fig. 1. This study we used convolution layer (Conv) with size filters 32(3x3), 64(3x3), 128(3x3), 256(3x3), and 512(3x3). Max pooling layer for this study we used (2x2) filters. For fully connected layer we used size 256,512 and dropout layer 20%. Process classification algorithm CNN we used image input 160 x 160 pixels with format images is RGB.

C. Introduction to Data Sets

The Plant Village Database is an images data set that contains plants diseases classes from. In the study, we used the data set in the process of classification tomato diseases plants. Tomato disease classes were used for 6 classes of diseases. The data set consists of tomato plants diseases that can be classified as bacteria, virus, and fungi. Where it consists of 100 images for training data and 10 images for test data for each class. The image in each class is 256 x 256 pixels with images format that is RGB.



(a) (b) (c)

(d) (e) (f)

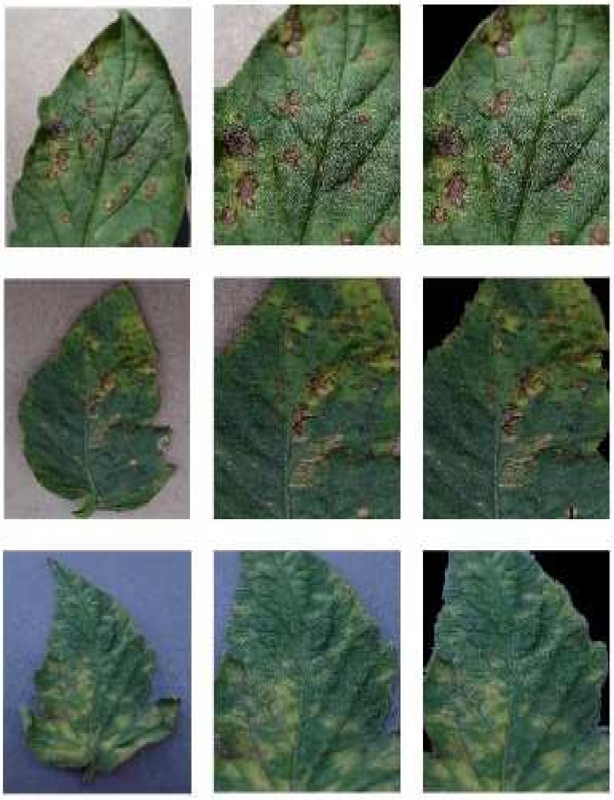
Fig. 2 Sample Images from The Classes

Fig. 2 is a sample of 6 types of tomato leaf disease found in the data set used. The cause of the disease in the leaves is because there is an attack of fungi, viruses, and bacteria. The diseases consist of Fig 2 (a) bacterial spot, Fig. 2 (b) early blight, Fig. 2 (c) late blight, Fig. 2 (d) leaf mold, Fig. 2 (e) yellow curl, and Fig. 2 (f) mosaic virus.

D. Image Enhancement

The process of improving image quality has a goal to improve the characteristics of the image that is owned and can produce a good classification process. The results of improving image quality will be used for data training and data testing. This process begins with resizing the image, then removal background it by removing the background from the image, the blending images process with canny filters where it aims to get the lines on the leaves to strengthen the image features and the last stage is data augmentation.

The cropping process is the initial steps that is carried out before going to the segmentation stage. Cropping aims to confirm the object in the images of the surrounding background by doing a smaller size intersection, so that an image is obtained with an object that almost fills the entire surface of the images.



(a) (b) (c)

Fig. 3 (a) RGB Images, (b) Cropping Images, (c) Background Removal Images

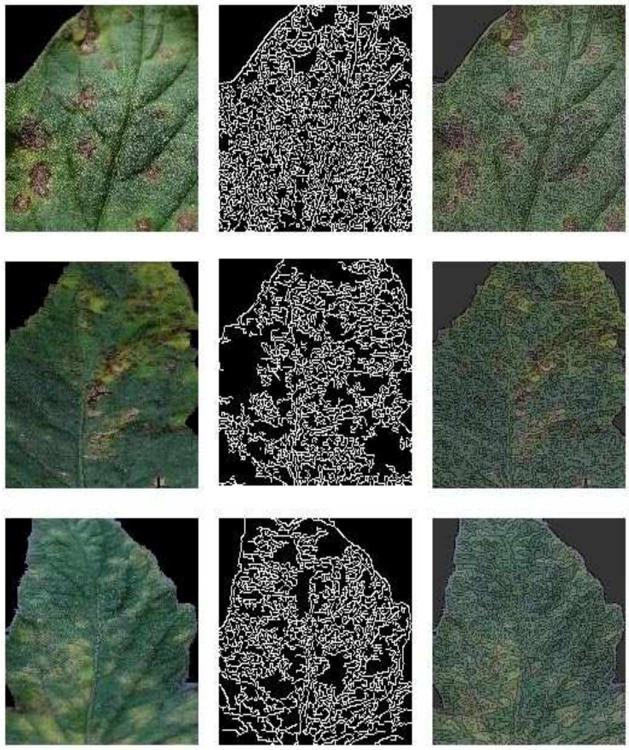
Fig. 3 (a) is the original images stored in the data set. While Fig. 3 (b) is the result of the cropping process which can be seen that the leaf object almost fills the entire surface of the image. Cropping process is carried out by changing the original image size format which is 256 x 256 to 160 x160 images size. After the cropping stage, a background removal process is carried out which aims to remove the background on the object

The results obtained are only objects without disturbing the background of the object. These results make the training process produce the optimal model for the next process of recognition. Fig. 3 (c) is the results of a background removal process.

Enhancement images quality can be carried out with a process with edge detection. Edge detection is widely used in applications during preprocessing preparation to cancel images by removing noise, then find image gradients to consider areas with high spatial derivatives, so searches will search throughout the region and touch screen changes [19]. The canny algorithm has to rule for using multiple thresholds by setting a low high threshold, if the gradient of the pixel magnitude is greater than the high threshold, the height is used as the edge, otherwise if the lace is higher than the non-edge point [20].

Blending images are carried out to sharpen the features possessed by the original image. The process is carried out with the blending images with a blend of the original image and the addition of the desired feature bumps.

In this paper the blending process is carried out between the original RGB image and detecting the edge of canny. From this, we can predict the results of the blending images in the form of an RGB images with the highlight or sharpening of the lines on the leaves.



(a) (b) (c)

Fig. 4 (a) Background Removal Images, (b) Canny Filter Images, (c) Blending Images

Fig. 4 shows the results of the canny process and blending images. The image used to do canny detection is the cropped image. The canny process is carried out to detect edges in leaves diseases. The results of the canny process are shown in Fig. 4 (b). The first process is to change the RGB images into a grayscale images and continue to determine the low and high thresholds, the results obtained in the form of black and white images. Fig. 4 (c) is the results of the blending process between the original images and the canny result images. Fig. 4 (c) that the features of leaf diseases are slightly more prominent than the original images data.

The classification of tomato diseases using a data set of tomato leaves diseases where images quality is needed so that during the training process the data produces optimal results, therefore an augmentation process is needed. One of implementing for image enhancement is using data augmentation. Augmentation data is used so that the images on the data set have a variety of images so that during the training process the features of the images are better to recognize.

TABLE II
RESULTS OF TESTING

No	Dataset	FAR	FRR	GAR
1	RGB Images	3.3%	6.7%	93.3%
2	Blending Images	16.7%	20.0%	80.0%
3	RGB & Blending Images	3.3%	3.3%	96.7%

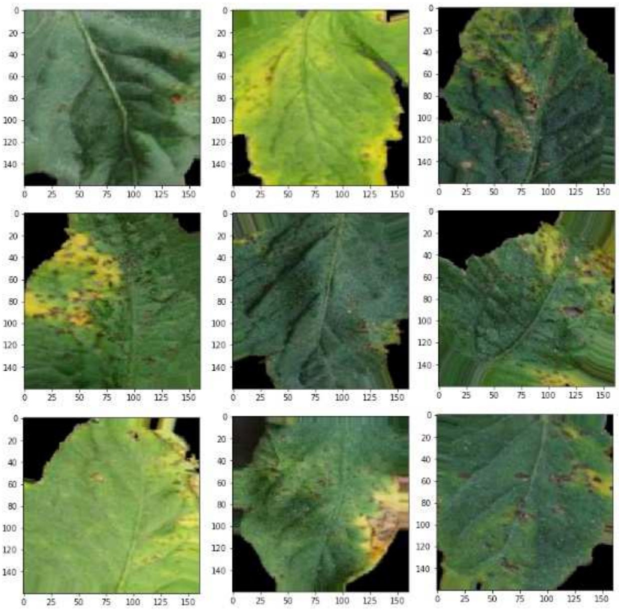


Fig. 5 Data Augmentation

In this paper, the classification process in the training phase used augmentation to add images to be more varied. The augmentation process is used like a zoom range, rotation range, horizontal flip, and vertical flip. Fig. 5 is the result of the augmentation process that has been carried out. After the augmentation process, it is continued with the data training process using the application of CNN.

III. RESULT AND DISCUSSION

A. *Classification Result*

Classification is carried out using test data that has previously been prepared. This test is carried out to identify the test data that is entered whether it is compatible with the disease from the data. Research in the proposed testing, after the stage of getting accuracy, each image is then preprocessed using the threshold to find the percentage of False Acceptance Rate (FAR) is measurement of the percentage faulty recognized individuals, False Rejection Rate (FRR) is used to measure model performance when operating in the classification and usually calculated as the percentage a false reject, and Genuine Acceptance Rate (GAR) is the percentage of genuine matches [21]. The proposed threshold is from 1 until 100.

$$FAR = \frac{\text{Total Number of Diseases Classifier with Another Disease}}{\text{Total Number of Test Images Samples}} \quad (1)$$

$$FRR = \frac{\text{Total Number of Correctly Recognized Diseases Reject}}{\text{Total Number of Test Images Samples}} \quad (2)$$

$$GAR = 1 - FRR \quad (3)$$

The testing phase was carried out with several experimental efforts using RGB data sets that had previously been carried out by the image enhancement process to obtain optimal results. Data training used 3 different types of data sets, consisting of original image RGB, blending images, and a mixture of RGB images and blending images. Based on the results obtained, blending images with RGB images during the training model making process showed better results among all experiments. The results of FAR and FRR in each data set we display based on the tests that have been carried out.

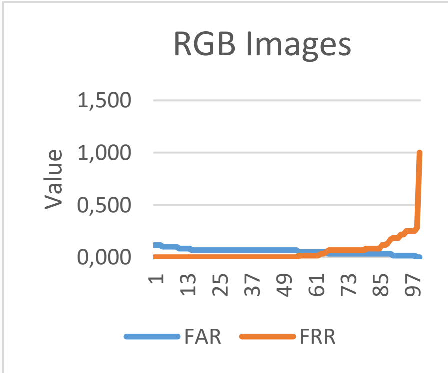


Fig. 6 RGB Images Chart

Fig. 6 is the result of testing using an RGB images data set. The results of the test are visualized using chart lines. This visualization displays the results of FAR and FRR calculations using the threshold of 1 to 100. At the threshold 1 the value of FAR is 0.117 while FRR is 0.000. Until the final limit, the threshold of 100 gets the FAR value of 0 and FRR of 1. A meeting occurs between the FAR line and the FRR line on the 65 thresholds by getting a FAR value of 0.033 and FRR 0.067. The results of the acquisition can be calculated to obtain a GAR value of 0.933.

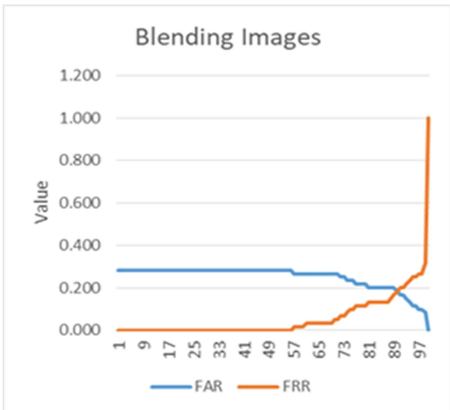


Fig. 7 Blending Images Chart

Fig. 7 is the result of testing using data set blending images. This visualization displays the results of FAR and FRR calculations using the threshold of 1 to 100. At the threshold 1 the value of FAR is 0.283 while FRR is 0.000.

Until the final limit, the threshold of 100 gets the FAR value of 0 and FRR of 1. A meeting occurs between the FAR line and the FRR line on the 91 thresholds by getting a FAR value of 0.167 and FRR 0.200. The results of the acquisition can be calculated to obtain a GAR value of 0.800. The results obtained are still not optimal compared to using the RGB images data set.

Fig. 8 is the result of testing using a mixed RGB Images data set and. This visualization displays the results of FAR and FRR calculations using the threshold of 1 to 100. At the threshold 1 the value of FAR is 0.067 while the FRR is 0.000. Until the final limit, the threshold of 100 gets a FAR value of 0 and FRR of 1. A meeting occurs between the FAR line and the FRR line on the 93 thresholds by obtaining the FAR value of 0.033 and FRR 0.033. The results of the acquisition can be calculated to get a GAR value of 0.967.

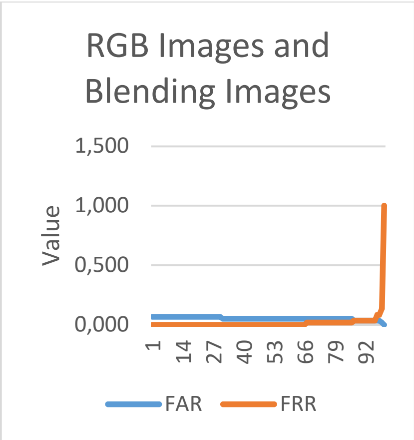


Fig. 8 RGB Images and Blending Images Chart

The results obtained based on the testing process, where the data training model uses mixed RGB images and blending images get the most optimal value in this classification.

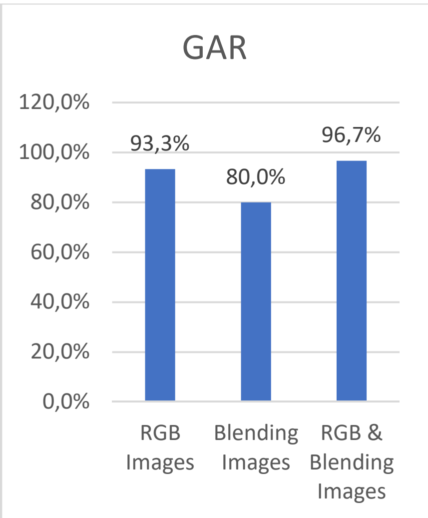


Fig. 9 Chart GAR

Fig. 9 shows the percentage of GAR regarding the accuracy of the trained model in recognizing images. Trained mixed image blending and RGB images models get the highest score among others with a gain of 96.7%.

Based on the results in Table 2, it is a list of the convolutional neural network models with 3 training experiments. Mixed blending images and RGB images can be analyzed as the best training model in this test. The process of running the program using the CNN algorithm requires a processing time of 35 minutes which is used for the training process of data and the classification process

IV. Conclusions

Recognition of tomato disease implemented with CNN was carried out in two stages, namely the training process and the testing process. Diseases images data for each class in this paper used the Plants Village data set for each class using 100 images used for training and 10 images used for testing. The image obtained is carried out by the process of improving image quality, which is then used to testing data and training data using the Convolutional Neural Network (CNN). The image enhancement process occurs several times which starts with resizing the image, removing the background, clever filter, and image blending. Furthermore, the data is stored which is used for training and testing data. Before the data training process, images blending results were carried out by data augmentation process that aims to make the image of each class diverse so as strengthening the results obtained. The training data will be stored and then used for the data testing process. Testing is finished by conducting experiments on 3 data sets with RGB images, Canny Blending images, and blending images and RGB combinations. The results of testing in the recognition process are displayed with the percentage of FAR, FFR and GAR. The results obtained from these three processes where mixed RGB and Blending Image have a greater percentage a Genuine Acceptance Rate (GAR) than the others are 96.7%. So in this paper using mixed RGB and blending image in the data training process can optimize training models so that the recognition process is more accurate.

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