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Investigation of RGB to HSI Conversion Methods for Early Plant Disease Detection Using Hierarchical Synthesis Convolutional Neural Networks

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***Abstract*— An early detection of disease can save the plant. One of the ways is by using eye-observation, which is time-consuming. Having a machine learning technology that can automate early detection would benefit modern and conventional farming. This study emphasizes the review of Hyperspectral Image (HSI) reconstruction using the Hierarchical Synthesis Convolutional Neural Networks (HSCNN) based method in early plant disease detection. Capturing hundreds of spectral bands during image acquisition enables the HSI capturing devices to provide more detailed information. Detection of disease with Red Green Blue (RGB) images needs to be done when it shows a notable spot or sign. However, the disease can be spotted with the correct range of spectral bands on HSI before a notable spot or sign is shown. The usage of HSI image is significantly important as it is rich in information and properties needed for image detection. Although HSI device is significantly important in early plant disease detection, the devices are expensive and require specialized hardware and expertise. Thus, reconstructing the Reg Green Blue (RGB) image to HSI is required. This research implemented two types of HSCNN-based methods, Densed network (HSCNN-D) and Rectified Linear Unit network (HSCNN-R), for HSI reconstructions. The results show that HSCNN-D outperformed the HSCNN-R with less Mean Relative Absolute Error (MRAE) of 2.15%.**

***Keywords*— Plant disease detection; hierarchical synthesis convolutional neural networks; machine learning; flexible rectified linear unit network; deep learning.**

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I. INTRODUCTION

A healthy plant is crucial in the production and quality of crop yield. However, to ensure high quality of crop yield, farmers need to deal with a plant disease that is recognized as one of the factors affecting the production. The effect of the disease is different according to the causes of the disease that can be minor to major serious damage, which can damage the entire crop field [1]. Therefore, using chemical substances such as fertilizer, pesticide, and herbicide can help overcome or control plant disease [2]. However, the inefficient or excessive use of chemical substances and resources can result in residual effects and toxicity that affect human health and the environment [3]. Besides, improper way of plant disease detection can also lead to major financial costs and heavily impacts the agricultural economy [4]. So, a proper plant disease detection approach needs to be applied as it can help the farmer take proper action and plan the usage of their chemical substance to overcome the plant disease problem.

A few approaches can be used to detect plant diseases, such as Machine Learning (ML) technique or visual observation approaches. However, manual approaches like visual observation, samples collection, and laboratory diagnosis are usually time-consuming, difficult, and error-prone, mainly in a large field [5]. Applying the ML approaches in disease detection can save time and effort, achieve real-time judgment, and reduce the loss caused by diseases [6]. In plant disease detection, early detection of disease would be beneficial as it can give information to the farmer, which acknowledges them to take early action and intervene before the disease is spreading into another field or plant. Thus, it can save the farmers from a huge loss. If this is done manually, it will require effort and time.

A huge amount of plant disease detection had been made using the ML approaches and had succeeded in achieving high accuracy of the detection result [7]. There are two common types of images usually used: Red Green Blue (RGB), and Hyperspectral Image (HSI). The HSI device captures images with narrower spectral bands or hundreds of spectral bands, thus providing more detail [8]. Thus, a special device that produces HSI is used in image acquisition. With RGB images, the disease is detected when it shows a notable spot or sign [9]. On the other hand, the disease can be spotted with the correct range of spectral bands on HSI before a notable spot or sign is shown [10].

Despite providing valuable information on plant disease detection, the HSI device is expensive and requires special hardware and expertise. Researchers were trying to use the RGB image by inventing several techniques for HSI construction. In plant disease detection, the HSCNN-based method is chosen widely. Therefore, this research will extensively review the previous research done in plant disease detection, focusing on the conversion technique in the pre-processing part of the overall disease detection stages. The research will discuss plant disease detection methodology in section 2, HSI properties in part 3, RGB to HSI conversion by using HSCNN in section 4, and Discussion in Section 6.

II. Materials and Methods

A. Pre-processing

In plant disease detection, the first stage of the process that is needed to be done is pre-processing. In the pre-processing activities such as data collection and data augmentation, noise removal is done to ensure that the images are fed into the detection system. Kumar [11] has classified plants into healthy and unhealthy. In their research, Plant Village Dataset that consists of 54,303 healthy and 50,000 healthy plants were used. Hassan et al. [12] has also used the same dataset to identify plant disease. Data augmentation is implemented to ensure an effective classifier can be obtained. The image can be flipped into vertical or horizontal form in the augmentation process. Various angles and scales of the image can also be done through rotation.

B. Segmentation

The homogenous region of the disease and non-infectious portion need to be separated. The segmentation process can achieve this process. Several techniques of segmentation have been done previously. A two-stages of K-means clustering was applied by Baghel and Jain [13] to segment the diseased part of leaves. In their research, the shading and spatial elements of the pixels were used to cluster between the two areas (infected and non-infected). The following feature extraction process is discussed in the following subsection.

C. Feature Extraction and Classification

Feature extraction is a type of image segmentation in which the important aspects of a region in an image are extracted to distinguish it from another region. Feature extraction is a broad term that can be defined as the search for areas with specified qualities, such as corners, but it can also refer to any set of measurements, whether scalar, vector, or other. These characteristics are frequently employed in pattern identification and detection. Normally, a processing approach for plant disease detection would be to segment off plant cells from an image, characterize their form using edge smoothness criteria, and then distinguish normal from diseased cells.

D. Hyperspectral Image Properties of Plant

Hyperspectral images show spatial information without the chromatic compression seen in digital cameras, preserving the spectral characteristics of the object source, which is essential for detection research [14]. HSI is a non-invasive imaging technique that employs visible and near-infrared light. HSI has a bigger band or wavelength range value of 400 nm to 2500 nm to quantify differential reflection in chemicals or biological molecules [15]. HSI has been used vastly since its ability to supply rich information. Remote sensing [16], health care [17], wood characterization, and the food sector [18] are benefiting from fast, ecologically friendly, and non-invasive examinations from hyperspectral devices. The hyperspectral image usually is acquired from a hyperspectral device, as shown in Fig.1. There is no compression of the visual information as digital cameras do [19].

Fig. 1 SPECIM IQ sensor mounted on a tripod (left). (right) A close-up of the SPECIM IQ sensor [10].

Hyperspectral devices maintain the spectral properties of the light signal in the waveband, which are relevant to the research focus object. Through hyperspectral imaging, the early stage of the plant disease can be detected (Nguyen et al., 2021). Among the plant, disease techniques are SVM, 2D-CNN, and 3D-CNN.

The reconstruction of RGB images to HSI strongly depends on the image lighting [20]. Therefore, developing good neural network models is necessary to train datasets that span a wide range of illuminations to help encounter this issue. Another approach for dealing with varied lighting is normalizing the RGB pictures using a white-balancing method before training the network [17].

The neural network’s performance is affected because the spectrum of a hyperspectral image is acquired at different wavebands or wavelengths than an RGB image. As a result, it is critical to determine relevant wavelength waves for Plant Disease detection [16]. As in Table I, some of the healthy and infected plant features have been acquired.

TABLE I
PLANT CRITERIA

No	Healthy Plant [24]	Infected Plant [28]
1	Low reflectivity at visible wavelengths	Changes in tissue color
2	High reflectance at near-infrared wavelengths	Changes leaf shape
3	Low reflectance across a wide range of wavelengths at short-wave infrared wavelengths	Changes transpiration rate
4	-	Changes canopy morphology

This metabolic modification will very probably be reflected in a certain reflectance waveband due to the metabolic alteration. An early diagnosis of plant illness can be made by using the range value of 500 nm–700 nm [21]. Another alternative is red-edge wavelengths, which can be used in a wide range of applications.

E. RGB to HSI Reconstruction Method

A deep learning method for RGB to HSI image reconstruction has been done by [18] to evaluate the tomato quality. The research adopted the advanced residual neural network HSCNN-R [22]. The advanced HSCNN-R is made in order to solve the limitation of the original HSCNN.

F. HSCNN model

Up-sample function, convolution, kernel size, and activation function are all part of an HSCNN model. The network's architecture is depicted in Fig. 2. The convolution is marked by the letter "C" surrounded by a rectangular block, and the kernel size is indicated by the numbers "1" and "3" that appear after the letter "C." (i.e., 1 1 and 3 3 correspondingly). The Rectified Linear Unit (ReLU) activation function is represented by the letter "R." Concatenation is represented by the letter "C" enclosed in a circular block. This annotation is also present in Fig. 3 and 4.

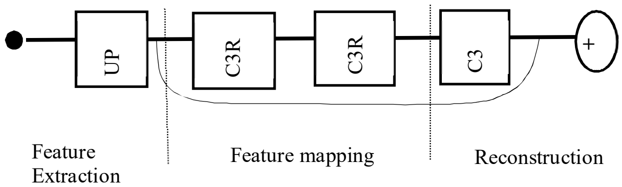

Fig. 2 HSCNN Model

The steps involved in HSCNN are:

- Step 1: The interpolation procedure is used to upsample the RGB input to produce a spectral form image.
- Step 2: Upsamples are stopped once the desired number of bands determined by HSI is reached.
- Step3: As an input to the network, use the spectral upsampled image as a starting point.
- Step 4: Learns a stack of convolutional layers and uses them to predict the missing residuals.

In order to perform spectral upsampling, it is necessary to have some idea of the spectral response function. When the spectral response is unknown, an HSCNN cannot be used [23]. As a result, they replaced the spectral upsampling with HSCNN-U, a simple convolutional layer with a sampling frequency of 1x1 and no bias.

G. Hierarchical Synthesis Convolutional Neural Networks SCNN-Dense

Hierarchical Synthesis Convolutional Neural Dense Networks (HSCNN-D) is a modified standard HSCNN to enhance the basic HSCNN. In the HSCNN-D, the structure of the model is developed densely. The features from the nth current layer will be processed to the next layer with the dense structure. Several issues that are overcome by using HSCNN-D are listed below:

- Lighten the vanish gradient during training
- Improve the performance while increasing depth and network.
- Provide adequate computing resources.
- Increase the channel number between the input and output gap enables the model to learn ineffectively.

The HSCNN-D model is shown in Fig.3.

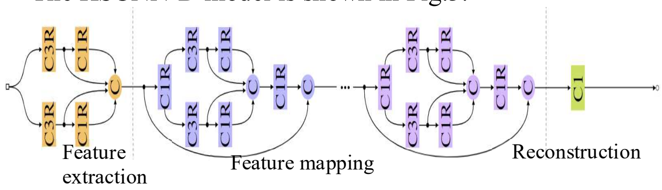

Fig. 3 HSCNN-D Model

The plant disease has a variety of spectral bands of RGB elements that can be in a range of (500 nm –700 nm) with uneven light conditions [21]. The HSCNN-R can work with unspecified spectral bands and different image illuminance; this is good for real-world images with unpredictable light conditions.

H. HSCNN-R

The HSCNN-R model replaces the HSCNN's traditional convolutional architecture with a modern residual block [30], keeping global residual learning while boosting performance. Before the image loses detail, the HSCNN-R model will be trained to a certain range of spectral bands. The architecture of HSCNN-R is shown in Fig. 4.

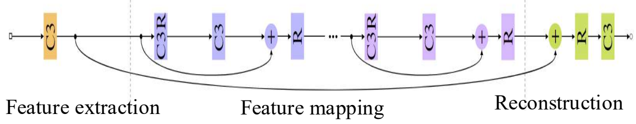

Fig. 4 HSCNN-R Model

For vein visualization, HSCNN-R was utilized to convert RGB images [17]. The purpose of this model is to sample the RGB picture spectrally up to n bands in a specified portion of the electromagnetic spectrum. The HSCNN+R was used to conduct a study on the quality of tomatoes [18]. HSCNN's simplistic CNN architecture was replaced with a more sophisticated residual block developed specifically for this purpose. In place of the 16 residual blocks originally recommended, six residual blocks with 64 filters were added to the HSCNN-R model to increase time effectiveness without affecting performance during the validation phase. During the model selection process, the permutation test was used to randomly partition 36 samples into two groups: a training dataset (24 samples) and a testing dataset (12 samples). It was done five times for each group of samples. In HSCNN-R, the batch size, learning frequency, learning frequency degeneration, and optimizer weight initialization were determined [23].

There are advanced models of HSCNN called HSCNN+, which consist of HSCNN-R. It adds the residual block and HSCNN-D, which uses dense blocks. Both models are proposed to improve the performance of HSCNN, which has limitations in the actual world image, with unspecified value on the spectral band and with different image illumination [23]. It is different in terms of performance and detail for the outcome from both models. HSCNN-R has better performance, thus which is faster than HSCNN-D. However, HSCNN-R is a bit loose in detail than the HSCNN-D, giving more detail but much slower performance [23]. Therefore, there is some trade-off between these two models.

The different models used for conversion of RGB image to HSI and its improvement of HSCNN model are shown in Table II. All the research focuses are different in each column but use the same model of HSCNN [23]. Each of the previous researchers had made some improvement in their research. It is either to improve the performance or for faster training.

TABLE II
COMPARISON OF HSCNN MODEL

Research Focus	**Vein Visualization [23]**	**Quality of Tomato [24]**	**Sceneric Image [29]**
Improvement	Adding the Batch Normalization	HSCNN's simple CNN architecture is replaced by six residual blocks.	Adding dense structure
Result	Faster training than previous HSCNN-R	Improving the time efficacy of the validation procedure without compromising performance	Improve the performance by increasing the depth of the network.

III. RESULTS AND DISCUSSION

After the development process was completed, we proceeded with the evaluation to compare the result of the plant disease detection between the converted and unconverted images. The percentages of validation accuracy for both results were evaluated to see which performs better for the early plant disease detection. Equation (1) for Mean Relative Absolute Error (MRAE) and equation (2) Root Mean Square Error (RMSE) is the standard evaluation method used in the HSI image reconstruction.

$$\text{MRAE} = \frac{1}{n}\sum_{i=1}^{n}(|I_R^{(i)} - I_B^{(i)}|/I_B^{(i)}) \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(I_R^{(i)} - I_B^{(i)})2} \quad (2)$$

In each of the HSI images,
$I_C^{(i)}$: Pixel of the conversion (i^{th})
$I_B^{(i)}$: Pixel of the bench marked image (i^{th})
n : Total number of pixels.

By examining this script, it is possible to establish whether or not the proposed model can outperform the prior HSCNN-R model in terms of overall performance and efficiency. We perform two experiments to test the performance between HSCNN-D and HSCNN-R. The results are presented in Table III. For the experiments, we used data that we acquired from the Kaggle website. The name of the dataset is *"NEW PLANT DISEASE DATASET V2"*, which consists of 14 types of fruits plants. For our research, we only choose apple images of 500 images. The sample of the datasets is presented in Fig. 5.

We used the method of RGB to HSV by an established work by Sabri et al. [24] as a benchmark HSV image. We name the dataset as benchmark data denoted as I_B in (1) and (2). For the training and testing, we use the same setting for HSCNN-D and HSCNN-R. The batch size is set to 64, optimizer Adam with β_1=0.9, β_2=0. 999 and ε=$1x10^{-8}$. The initial learning rate is set to 0.001. The training stops at 1000 epoch. The results show that the MRAE for HSCNN-D is less than HSCNN-R while the RMSE of both methods is almost the same, which differ at only 0.202. In terms of running time, the HSCNN-R has produced results faster compared to HSCNN-D. The experiments were done on CPU performance of computer specification Core (TM) i7-10510U CPU @ 1.80GHz 2.30 GHz due to lacking GPU.

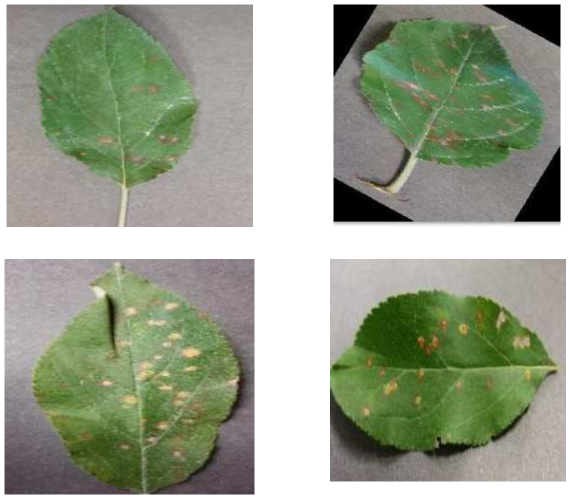

Fig. 5 Example images from *NEW_PLANT DISEASE V2* dataset

TABLE III
EXPERIMENTS RESULT OF HSCNN-BASED METHOD

Method	**MRAE**	**RMSE**	**Running Time**
HSCNN-D	0.0215	15.723	109s
HSCNN-R	0.0221	15.521	98s

Although the results of HSCNN-R are slightly less performance than HSCNN-D, it can run faster. In the work that has been done by Qiu et al. [25], the flexible RELU is introduced by modifying the standard RELU. They have discovered that the modification has produced the residual network's competitive and fast performance. Therefore, in the future, we suggest inducing the HSCNN-R with HSCNN-FRELU and testing the output for plant disease detection. It is due to the simplicity of the HSCNN-R.

IV. CONCLUSION

This research has presented an investigation of the HSCNN-based method for early plant disease detection, emphasizing the hyperspectral image reconstruction from RGB images. We used HSCNN-D and HSCNN-R to compare the performance of HSI image reconstruction from RGB images. It is concluded that both HSCNN-R and HSCNN-D have comparable performance in producing the HSI reconstruction from RGB image in terms of MRAE and RMSE.

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