Herbal plant leaves classification for traditional medicine using convolutional neural network

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ABSTRACT

The classification of herbal plant leaves can be implemented in agriculture and traditional medicine. Primarily, sorting leaves was done before it was processed into medicinal ingredients. Currently, the sorting was still done manually by writing it on notes. Sometimes there were errors in the selection of leaves for medicinal ingredients. Herbal plants had various forms and are very greatly. Artificial intelligence technology was needed to have fast-paced time efficiency in sorting leaves. In the field of artificial intelligence, there was a specific or detailed learning process known as deep learning. The objective of this research was to classify herbal plant leaves images by applying and combining the convolutional neural network (CNN) deep learning method with data augmentation methods without the pre-trained architecture such as MobileNet and LeNet. This technique consisted of 4 main stages such as collecting data, preprocessing or normalizing data, building a model, and evaluating. The dataset used in this research were 4 types of herbal plants that do not flower and do not bear fruit including gulma siam, piduh, sirih, and tobacco. Each class had 250 images with total dataset used in this research was 1,000 images of herbal plant leaves and divided into 2 data, namely 80% data training 20% data testing, and validation. The data was trained with the epoch of 100 for the best training. It had an accuracy score of 98.74%. Without the data augmentation process it had an accuracy score of 91.43%.

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1. INTRODUCTION

Herbal plants have an important role in traditional and alternative medicine. Herbal plants have been used around the world for centuries to maintain health and treat various ailments. Medicines from herbal plants have been used in the past 5,000 years ago by many people from around the world such as India, China, Egypt, Greece, Rome, and Syria. Many scientists currently study the scientific aspects of herbal medicine to extract meaningful information. It can give contribution to the development of modern medical science through research on the chemical content in herbal plants [1]. Nearly 80% of people still depended on traditional medicine. This happened because modern medical treatment in hospitals was not accessible to everyone and was expensive compared to traditional medicine. Accordingly, the existence of traditional medicine using herbal plants can help people with limited access. Herbal plants also have many benefits for human life as a provider of oxygen, foodstuffs, medicines, and cosmetic ingredients [2]. In modern medicine such as essential oils were made from herbal plants and had been widely developed. The ingredient of essential olis have shown anti-inflammatory, antioxidant, antibacterial, and antifungal properties [3].

Herbal plants have been used around the world for centuries to maintain health and treat various ailments. Plants certainly provide food for all living things, so plants are called the backbone of the ecosystem [4]. Based on previous research data, there are about 35,000–70,000 plant species used in traditional medicine worldwide [5], there are almost 10,000 plants used for any use categories to maintain health and treat various ailments. The benefits of plants based on the human knowledge cannot be separated from the contribution of local knowledge which had spread in various traditional societies. The use of plants as traditional medicine by local people was well-known and applied in daily life. Knowledge of this medical plant has been passed down from generation to generation through prior knowledge and experience [6]. However, in the modern era, many people were still mistaken in determining the types of herbal plants to be used in certain diseases. It happened because there were many species or types of herbal plants that have the same characteristics and even look very similar. To overcome this problem, it is necessary to have a system that can be used by modern people in order to classify and recognize various types and species of herbal plants through images of the leaves of these herbal plants.

Sorting of herbal plant leaves in traditional medicine, agriculture, and medical industries was deemed necessary to implement a method of classifying herbal plant leaves. This is due to the difficulty in distinguishing species or types of herbal plant leaves which look very similar. The leaves of herbal plants were widely used. One of which was as an ingredient for making traditional medicines. The importance of sorting herbal plant leaves using the deep learning method was to avoid mistakes in selecting herbal plant leaves as ingredients for making medicine. One of the most common deep learning applications in the field of image classification was the convolutional neural network (CNN) [7]. CNN could be a special variety of multi-layer neural networks impressed by the mechanisms of the optical system of living beings [8]. CNN is a deep learning model consisting of several layers convolutional, pooling, and fully connected layers [9]. CNN is widely used in many fields, applications, and problems in computer vision such as image recognition, segmentation, detection, and classification [10].

Previous research has used the CNN algorithm with optimization of CNN architectures such as MobileNet and LeNet. The objective of this research is to only use optimization of the CNN algorithm with the help of data augmentation best solution by using 4 types of herbal plants which they did not produce flower and fruit. They were gulma siam, piduh, sirih, and tobacco. Each of it had 250 images with total dataset used in this research was 1,000 images of herbal plant leaves which divided into 2 data, namely 80% data training 20% data testing, and validation. The CNN architecture implemented in this study was expected to be able to classify images of herbal plant leaves and produce the best accuracy.

There are five sections to this research. Section 2 presents research on the development of CNNs that has been carried out previously and used as a reference for this research. Section 3 describe method. Section 4 will be explain the results of the method. In section 5 were the final conclusions and things that could be done for further research.

2. RELATED WORKS

CNN is an algorithm that already exists but has been developed by several researchers in the field of deep learning. CNN is also well-established algorithm that has gained significant traction within the deep learning landscape. Over time, a series of studies have been dedicated to uncovering the potential of CNNs. Each of it uniquely designed to address diverse objects and domains. Its metamorphosis, orchestrated by a plethora of researchers, has propelled the frontiers of artifical intelligence research. This research is inseparable from previous research as a reference. The lineage of this study traces back to antecedent research, which forms the bedrock of theoretical and empirical knowledge. Several studies have focused on developing CNNs across a variety of objects.

Research by Lu *et al*. [11] classified fruits using CNNs. The objective of this research was to use CNN for fruit classification. They designed six layers of CNN consisting of a convolution layer, a pooling layer, and a fully connected layer. The results of the experiment achieved promising performance with an accuracy of 91.44%, better than three advanced approaches: vector engine voting-based support, wavelet entropy, and genetic algorithms.

Research by Zhou *et al.* [12] aims to address the problem of natural Apple classification. They built a large data set of wide Apple images with 79 classes and planned a brandnew framework supported by CNNs to classify flowers. The objective was to address the problem of natural Apple classification. The neural network consisted of five convolutional layers during the receptive planes square measure adopted little, the number of squares measured followed by a maxpooling layer, and three layers that are fully connected with the last 79-way softmax. They approach reached 76.54% brackets in the author's laborious Apple dataset.

Additionally, the algorithmic rule of the check authors on the Oxford was 102 Apple dataset. It outperformed the antecedently proverbial vogue and achieved the delicacy of the 84.02% bracket.

Research by Iftikhar *et al*. [13] presented a method of capable of recognizing tomato plant species in pictures coloured during a CNN way. The network was engineered from scratch by being trained and tested on a complete of 2,364 images. Into four types of different tomato leaf disease-infected high-resolution images. For these 4 type, this network was in the position to realize a classification accuracy of 99.6%. The aim of this study was to solving the problem of early identification/diagnosis of diseases.

Das and Yadav [14] created a tomato detection automation system using CNN. In this study, they were using 3 layers to produce a better classification. The training dataset used in this research was 80% of the total available dataset and the testing dataset used in this research was 20%. The results obtained from this system had an accuracy rate of 99.67%. This paper proposed an automated tomato maturity classification system that used CNN as a classifier. In CNN author model, three layers were included in achieving a better classification. The performance of model was very high compared to traditional approaches.

Rice plant detection was carried out in real-time from a height of 60 m–100 m with an accuracy rate of 86.5% and 87.8% respectively [15]. To increase the level of accuracy, artificial height images were used in this study so that at the same height, this system was able to detect rice plants with an accuracy rate of 99.6% for a height of 60 m and 99.7% for height of 100 m. The purpose of this study was to support farmers by estimating growth stage of paddy rice by using deep learning and normalized difference vegetation index (NDVI) images. In this paper, we compared growth stage classification accuracy using images taken at the different height of the drone.

Dong and Zheng [16] implemented CNN on the quality of enoki mushrooms. The total dataset used in this research was 23,000 images and the size of each image was 1280×1024. The level of accuracy obtained from this study was 98.35%. Experimental results demonstrated that CNN-driven classification application had higher recognition rate for enoki mushroom caps, which provided an important reference for the application of enoki mushrooms in agricultural automation production and helped to optimize yield and increased productivity.

According to Gustisyaf and Sinaga [17], the way toward distinguishing fingerprints was one of the significant, simple to did multifariousness strategies, the cost was cheap, and a dactyloscopy authority did the particular outgrowth. Classified gender by fingerprint was using CNN method. Three models were created to determine sex, with a complete of 49,270 image data that included in test data and training data by classifying two classes, male and female. From the three models, the very best accuracy was taken at 99.96%.

3. METHOD

Deep learning has emerged as a major tool for self-perception problems such as understanding images, sounds from humans, and robots exploring the world. One of the deep learning algorithms with the best level of accuracy is the CNN. CNN consists of 1 or more convolutional layers and so continued with one or additional utterly connected layers as in a very customary multilayer neural network [18]. Understanding CNN and applying it to image recognition systems is the target of the projected model. CNN extracts feature maps from the second image with a victimization filter. CNNs consider mapping image pixels with environmental areas instead of having entirely layers of neurons connected. CNNs have been tried to be very dominant and potential tools in the image process. Even at intervals in the areas of PC vision such as handwriting recognition, physical object classification, and segmentation, CNN has become a far higher tool compared to all or any different tools antecedently enacted [19]. In this research, the stages of the research carried out consisted of 3 stages referring to the machine learning method, starting from collection and preprocessing dataset, model building, and model performance evaluation.

3.1. Collecting dataset

The image data was taken manually using the phone's camera. It was collected 1,000 herbal plant leaves images and divided into 4 classes as labels with different pixel resolution sizes and different formats. The original images size were 947×583 pixel. Accordingly, all images were set into 256×256 pixel so that the images size become precise. The images were taken from a variety of different positions and used as data training for one type of herbal plant leaf. The format data of image was set to joint photographic expert group (JPEG). The images were divided into three parts, namely 80% training, 10% validation, and 10% testing. The examples of data used in this research can be seen in Figure 1.

All data used in this research was divided into 4 class folders with the labels gulma siam, piduh, sirih, and tobacco. Each class, there were 250 images of herbal plant leaves. Therefore, total dataset used in this research was 1,000 images of herbal plant leaves. Figure 2 process is data size normalization to 256×256.

Figure 1. Herbal plant leaves dataset

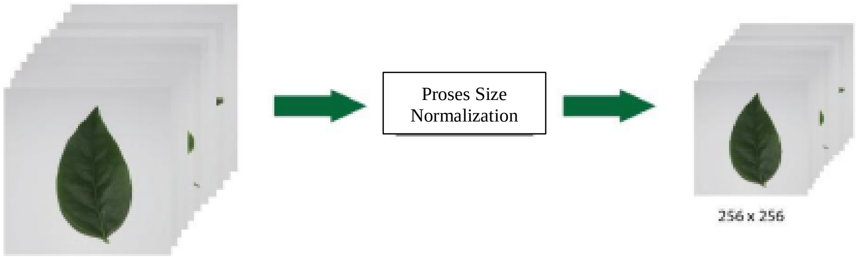

Figure 2. Size normalization

The process of size normalization of images was shown in Figure 2. As describe before, the size of images was reduce to 256×256 pixel from the original size. In the size normalization stage, resizing is carried out into its size so that the classification process can run more easily and efficiently. It was also obtained an equal image size for all images in the dataset. After all images were in the same size, it would be processed in the preprocessing stage to get better results.

3.2. Preprocessing dataset

Data pre-processing was an essential stage to maintain the diversity and smooth functioning of the algorithms [20]. Deep learning did well when the input data set was as large as possible and avoids overfitting. Very small changes, invisible to the human eye, such as adding noise and blur to the input image, could help CNN learn more advanced features [21], [22]. In this research, the dataset was augmented with Gaussian blur, salt and pepper noise with a random scale of 0.95 to 1.05 in the horizontal and vertical directions, and random rotation in the range of −30° to 30° of the images. The augmentation combinations used in this research were shown in Table 1. Other augmentations that were carried out in this research were done by rotating and flipping the dataset. In position augmentation, the image was rotated to 45°, 135°, 225°, and 315° then the image was flipped horizontally and vertically. Saturation, hue, and contrast color augmentation were added. Saturation represented the amount of purity or tint of a color. Hue represented a color (blue, red, and green); the value ranges from 0 to 360. Histogram equalization was performed in evaluating the contrast value on color augmentation. Histogram equalization was known to improve accuracy.

Table 1. Augmentation dataset

No. augmentation	Target	Algorithm
Augmentation 1	Noise	Salt and pepper noise
	Blur	Gaussian blur
	Position augmentation	Random scaling
		Random rotation
Augmentation 2	Position augmentation	45° rotation, 135° rotation, 225° rotation
		315° rotation, horizontal flip, vertical flip
	Color augmentation	Hue
		Saturation
		Contrast

Augmentation dataset in Table 1 was a combination of data augmentation used in this research to create the best CNN model classification of herbal plant leaf. The dataset contained 1,000 images and an augmented dataset of 10,000 images with 4 types of herbal plant. The deep learning network utilized in this research was proposed by CNN. Input images were resized to a size of 256×256×3 for the developed and proposed models.

3.3. Proposed convolutional neural network

The convolutional layer is the central part of CNN. The image area unit was usually stationary. The formation of one half of the image is the same because of the remainder of the half. The features studied in one region would have similar patterns in another. The filter area unit is designed to support the rear propagation technique. CNNs are currently the most numerous efficient models for classifying images [23]. CNN continues to increase its computing speed because hardware progress and the range of applications have developed gradually because it has proven its superior performance [24]. CNN showed good performance in the classification of objects. Almost all CNN architectures followed identical general style principles of in turn applying convolutional layers to the input, sporadically downsampling the spatial dimensions while increasing the number of feature maps. Moreover, there also were totally connected layers, activation operations, and loss functions [25]. However, among all the operations of CNN, convolutional layers, pooling layers, and absolutely connected layers were the foremost vital ones.

The convolutional layer was the initial layer where it would extract options from the pictures as a result of pixels area unit associated with the adjacent and shut pixels. Convolution permited to preserve the connection between completely different components of a picture. Convolution was filtering the image with a smaller picture element filter to decrease the dimensions of the image while not losing the link between pixels. When applying convolution to a 7×7 image by employing a 3×3 size filter with a 1×1 step would have a 5×5 as an output. When constructing CNN, it was common to insert pooling layers once every convolution layer, in order to cut back the abstraction size of the illustration. Layers reduced parameters and complexity. Also, pooling layers facilitated with the overfitting downside. The totally connected network was in any design where each parameter was connected to a different parameter to see the link and impact of each parameter on the label. The complexness of space-time continuum was reduced by victimisation convolution and pooling layers.

In general, CNN had 2 stages, namely the stage of learning features and classification. Feature learning was a technique that permits a system to run mechanically to see the illustration of a picture into options in the variety of numbers that gift the image. The bracket stage was the stage where the results of point literacy was used for the next process based on the intended sorting. Image input on the CNN model was a 256×256 in size. Feature learning consisted of two layers: the convolutional layer and the pooling layer [26]. The input image was processed through a convolution process and a pooling processed at the feature learning stage. Each convolution had a different number of filters and kernel sizes. The alignment process or the process of changing the feature map resulting from the pooling layer was carried out. The built CNN model was depicted in Figure 3. Without pre-trained architectures such as MobileNet and LeNet.

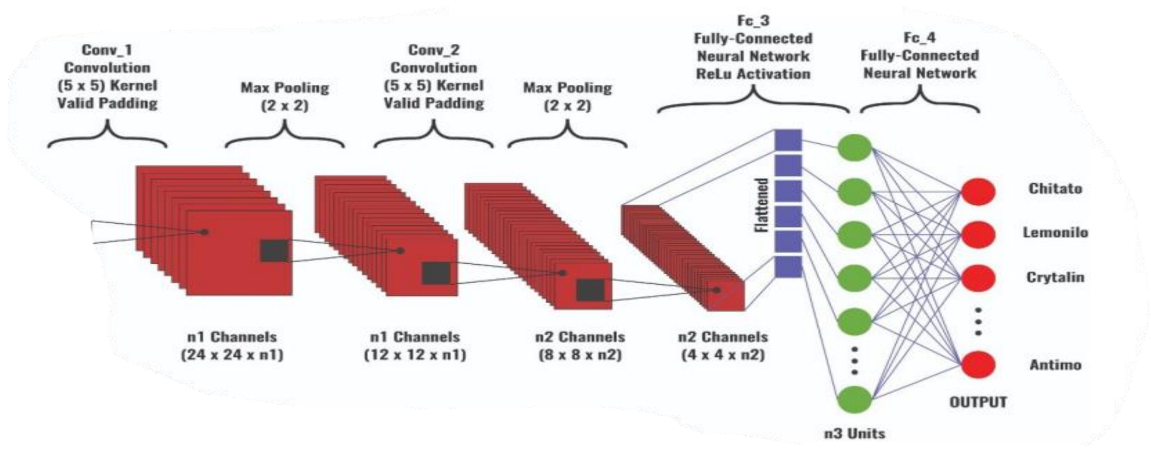

Figure 3. CNN architecture diagram

The structure of the CNN consisted of inputs, feature extraction, classification, and outputs as can be seen in Figure 3. The CNN model was built consists of 6 convolution layers with features measuring 3×3 and using the rectified linear unit (ReLU) activation function and dropout is used on the fully connected layer found in CNN. Max pooling used at a size of 2×2, then a flattening process was carried out. It was changing the output of the convolution process in the form of a matrix into a vector. It would be continued in the classification process using a multi-layer perceptron with the number of neurons on the predetermined hidden layer. The image class was classified based on the values of the neurons in the hidden layer by using the softmax activation function. The output of the connected end layer was fully fed to the softmax function [27].

4. RESULTS AND DISCUSSION

The training process for the CNN model was carried out for 100 epochs. Using 100 epochs in the training process, you could have the best level of accuracy in every step of the training. Furthermore, testing was carried out using test data for each class of the CNN model that has been created using the Adam optimizer. The results of the training data and validation accuracy were depicted in Figure 3. The graph shows the result of the training and validation accuracy. Figure 4. explained for the graph of accuracy in training and validation. The higher the epoch or train was done, the closer the accuracy was too perfect.

The training and validation movement had almost the same value and continued increasing. If the accuracy was increasing it would give the better result. However, it still needed additions to improve accuracy, as in Figure 5 which explained about the graph of training accuracy and validation for data loss. As the epoch gets bigger, the accuracy was decreasing. It can be concluded that the data loss was less than the valid data. thus, the training process would become more complex and was not burdened with loss of untrained data.

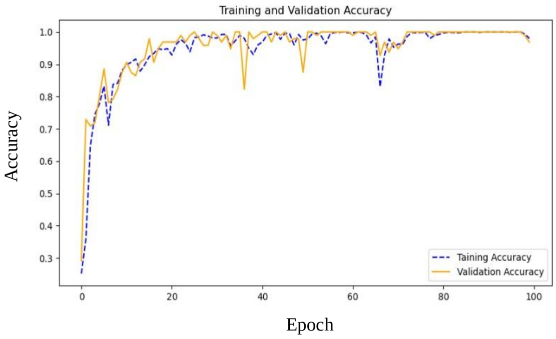

Figure 4. Training and validation accuracy

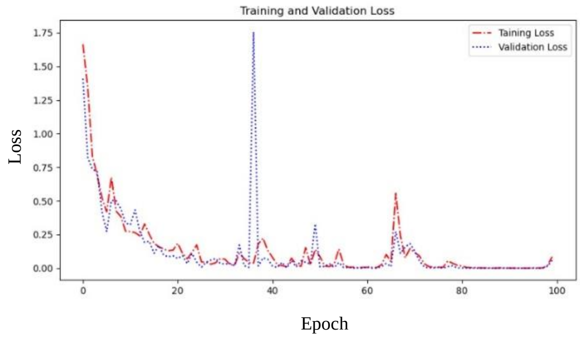

Figure 5. Training and validation loss

In Figure 5, it was depicted that the chart showed training and validation movements which were almost in line and decreasing. If the loss chart was decreasing, it would have the better result. The accuracy and loss were in the opposite direction which indicates that the data tested had run optimally. After testing using training data and validation data, testing was carried out using test data. Data loss and near-perfect accuracy could be produced. It could be proven in the test results and data validation as described in Figure 6.

Figure 6. Final results

The test results can be seen in Figure 6. The CNN model developed successfully classifies tobacco leaves with an accuracy of 97.35%, betel leaves with an accuracy of 100%, other tobacco with an accuracy of 99.97%, piduh leaves with an accuracy 100%, another betel leaf with 100% accuracy. The accuracy also reached very good and precise, by obtaining a final accuracy of 98.74% with an execution time of 1 hour including the data augmentation process, while without the data augmentation process the accuracy value was 91.43%. By combining CNN and data augmentation methods created without the MobileNet and LeNet architecture as in previous research, CNN can obtain very good accuracy for classifying herbal plant leaves. It is hoped that the methods used in this study can be used significantly to facilitate the work of sorting the leaves of herbal plants for any purposes in agriculture to the fields of modern and traditional medicine.

5. CONCLUSION

This study classified herbal plant leaves using the CNN method, which had been successfully carried out with an accuracy rate of 98.74% including the data augmentation process, while without the data augmentation process the accuracy value was 91.43%. The CNN model used 6 convolution layers with a filter size of 3×3, ReLU activation function, and softmax, using 2×2 layer pooling. The images used in this study were 1,000 images divided into 4 label classes with an image size of 256×256 pixels on a sequential model, with an epoch process of 100 for the best accuracy in the training process. It was hoped that this research can be further developed, such as combining feature extraction with the CNN model to get a better level of accuracy. It can also be implemented into devices such as websites and mobile as well as into drones so that they can detect with a wider range. Using CNN without using architecture such as MobileNet and LeNet. can provide positive value to the research field. As in this research, just using CNN without architecture has gained significant value and can still be developed further. CNN itself is the basis of existing architectures, so using CNN without architecture is the right choice in any research.

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