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# IMPLEMENTATION OF CNN FOR PLANT LEAF CLASSIFICATION

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**Abstract**
Many deep learning-based approaches for plant leaf stress identification have been proposed in the literature, but there are only a few partial efforts to summarize various contributions. This study aims to build a classification model to enable people or traditional medicine experts to detect medicinal plants by using a scanning camera. This Android-based application implements the Java programming language and labels using the Python programming language to build deep learning applications. The study aims to construct a deep learning model for image classification for plant leaves that can help people determine the types of medicinal plants based on android. This research can help the public recognize five types of medicinal plants, including spinach Duri, Javanese ginseng, Dadap Serep, and Moringa. In this study, the accuracy is 0.86, precision 0.22, f-1 score 0.23, while recall is 0.2375.

***Keywords:***
Leaf, Classification, Deep Learning, CNN



## 1. Introduction

Implementation of Deep Learning in agriculture has increased enormously in the last decade, including their use to classify different plant leaves. More recently, many deep learning-based approaches for plant leaf stress identification have been proposed in the literature, but there are only a few partial efforts to summarize various contributions [19]. Hence, there is a dire need for a detailed survey compiling techniques used to identify leaf stresses in various plants. Multiple methods of deep learning-based methods recently proposed for different crops using CNN architecture based on current works. The techniques reviewed were divided into vegetables, fruits, and other crops based on stress type, size of the dataset, training/test size and the deep network. The classification problem in agriculture issues is a new field to quickly introduce the deep learning application trend in plant leaf stress identification [18].

A study conducts classification as the process of finding a model or function that explains or differentiates a concept or class of data to estimate the type of an object whose label is unknown. The classification process is usually divided into two phases, namely the learning phase and the test phase. In the learning phase, some of the data known class of data is likened to model estimates. The stage of test models that have been formed is tested with most of the data to determine the model's accuracy. If the accuracy is sufficient, this model can be used for class prediction data is not yet known [1].

In the current time, various papers have proposed deep learning as a prospective solution to deal with many problems since several years ago. DeepProfile utilized features information obtained from social networks to deal with a social account to learn latent

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representations [5]. Other classification models also have been proposed to deal with several classification issues. Current techniques explore numerous works that collaborate with conventional techniques with a temporal model to establish a classification model [3][15][16].

The research introduced to move Machine Learning closer to one of its original goals, namely, Artificial NN, is a deep learning method applied to classify images. This method has been used, image recognition, computer vision, and Natural Language Processing (NLP). This paper constitutes a Deep Learning model as a new area in machine learning to deal with plant leaves classification. Based on the experiment, we obtain that a DL model can effectively classify plant leaves types using CNN architecture and present experimental results to convince the study result.

## 2. Related Works

Recently, Deep Learning has been in the spotlight in the development of Machine Learning. The reason is that deep learning has achieved excellent results in many areas [15][16]. It is a branch of Machine Learning inspired by the human cortex by implementing an artificial neural network with many hidden layers. CNN is one of the methods in deep learning to cover the previous method's weaknesses, employing manual feature engineering. There are several drawbacks in the previous method, but this model can reduce the number of independent parameters, and the input image deformation improves the translation, rotation, and scaling process [4].

Along with a lot of development and research on deep learning, many libraries have sprung up focusing on learning about artificial neural networks. Keras is a library of high-level neural networks written in Python and capable of running on TensorFlow, CNTK, or Theano [5]. This library provides features that are used to facilitate the more profound development of deep learning. A study discusses building a Javanese script classification dataset to help users detect Javanese characters. The result of this training is that the application of Javanese script classification can produce specific Javanese script pattern recognition rates in real applications [3].

A study discusses the status of occupancy by collecting a dataset of 2,146 houses and 370 empty houses. The classifier uses the Bayes classification to classify objects and implements the chi-square algorithm to measure the comparative data to the actual observed data. This study uses a combination of Naive Bayes and Chi-Square by applying weighting to the attribute dataset. The study concluded that the combination of algorithms could achieve promising results in classifying residential houses' status—the variety of the proposed techniques obtained an accuracy of 89.59% and a ROC-AUC value of 0.839. Therefore, the proposed model is better than the Naive Bayes standard without the combination with the Chi-Square approach [8].

A study discusses implementing a machine learning method for object image classification, namely CNN. The CNN method consists of two stages. The first stage is image classification using feedforward. The second stage is the learning stage with the backpropagation method. Before classification, pre-processing is carried out with the wrapping and cropping methods to focus on the object to be classified. Furthermore, training is carried out using the feedforward and backpropagation methods. The last is the classification stage using the feedforward method with updated weights and biases. The test results from the classification of object images with different confusion levels on the Caltech 101 database produce an average accuracy value. So it can be concluded that the CNN method used in this final project can classify well. [10]

In the plant leaf classification with traditionally handcrafted features is challenging to reveal its complex shape and texture. This paper proposed a novel leaf classification method based on CNN due to its robust feature extraction and classification capability. Based on the experiment, a ten-layer CNN was constructed for plant leaf classification. To improve the classification, they utilized sample augment for the leaf to the images to enlarge the database. The experimental results on leaf database Flavia with 4,800 leaf images and 32 kinds of leaf showed that the proposed method achieved a high overall accuracy with 87.92% [17].

## 3. Proposed Method

In this paper, we apply CNN architecture as a type of neural network usually used in the image data processing. Convolution, commonly known as convolution, is a matrix that functions to filter the image [6]. Convolutional Neural Network has several layers that are used to filter each process. The process is called the training process. There are three stages in the training process: the Convolutional layer, the Pooling layer, and the Fully connected layer.

In the CNN process, all features will be convolved in the convolutional layer to obtain the most informative features in each layer. The layer converts each filter to the entire input data section and generates an activation map or 2D feature map. The filter contained in the Convolutional Layer has a length, height (pixels), and thickness according to the input data channel. Each filter will undergo a shift and "dot" operation between the input data and the filter's value. The convolutional layer significantly experiences model complexity through optimization of its output. It can be optimized through three parameters, depth, stride, and zero padding settings [7].

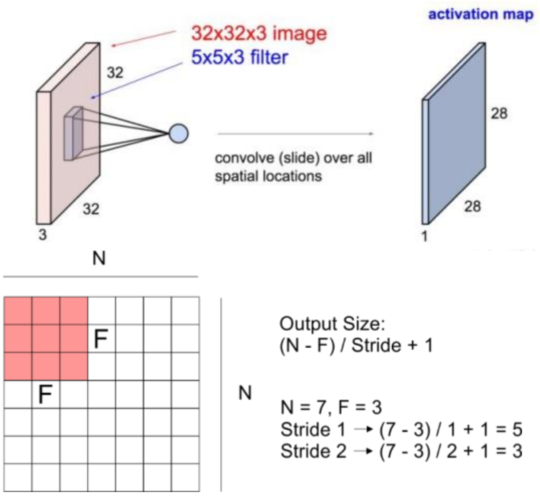


Fig.1 Convolutional Layer

We set the pooling stage after the Convolutional Layer with a filter with a specific size and stride in this phase. Each shift will be determined by the number of strides that will be shifted across the feature map or activation map area. In this paper, we implement Max pooling and Average Pooling with size 2x2 and Stride 2. Using Max pooling, the value is taken is the largest in the 2x2 area, and Average Pooling will take the average value of each feature map.

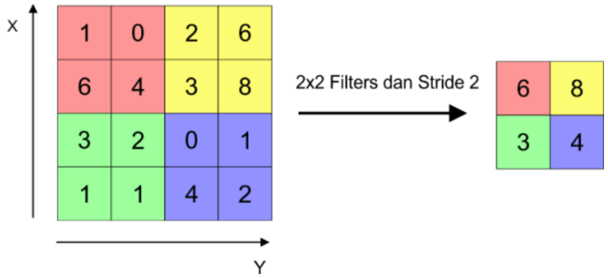


Fig. 2 Pooling Layer with 2x2 filter

Fully Connected Layer The feature map produced by the previous stage is in the form of a multidimensional array. Before entering the Fully Connected Layer stage, the Feature Map will go through a "flatten" or reshape process. The flatten process produces a vector that will be used as input from the Fully Connected Layer. Fully Connected Layer has several Hidden Layer, Action Function, Output Layer, and Loss Function.

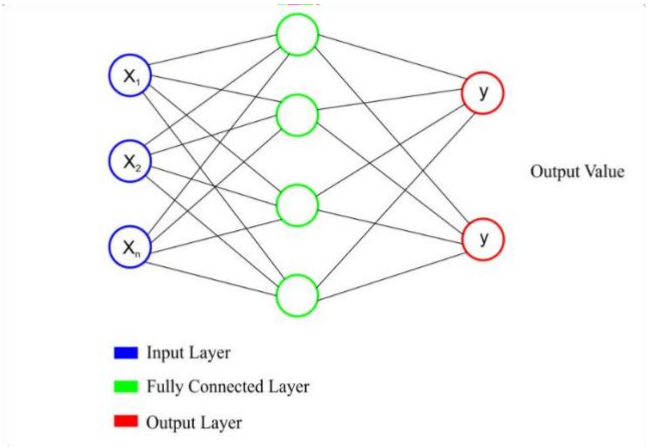


Fig. 4 Fully Connected Layer

The study utilizes Dropout to prevent overfitting and also accelerate the learning process [8]. Overfitting is a data condition that has gone through the training process reaches a good percentage, but there is a mismatch in the prediction process. In its working system, Dropout temporarily removes a neuron in the form of a Hidden Layer or a Visible Layer that is in the network.

In this paper, we conduct CNN to work with image data and their structure and function that should be less inscrutable than other types of neural networks. Specifically, the models are comprised of small linear filters and the result of applying filters called activation maps, or more generally, feature maps. Both filters and feature maps can be visualized. For example, we can design and understand small filters, such as line detectors, visualizing the filters within a learned CNN can provide insight into how the model works. The feature maps that result from filters to input images and to feature maps output by prior layers could provide insight into the internal representation that the model has of a specific input at a given point in the model. We will explore both of these approaches to visualizing a CNN filter size.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| -1 (x1) | -1 (x-1) | -1 (x-1) | -1 | -1 | -1 | -1 | -1 | -1 |
| -1 (x-1) | 1 (x1) | -1 (x-1) | -1 | -1 | -1 | -1 | 1 | -1 |
| -1 (x-1) | -1 (x-1) | 1 (x1) | -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 | -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 |


Fig 5. The input image subset with the kernel.

## 4. Experimental Setup

1. Creating a dataset
   We prepare all the required data for the image classification system on five types of medicinal plant leaves in this stage. The dataset is used as input which will then be processed at a later stage. In this study, the dataset used is the face94 dataset sourced from Dr. Libor Spacek. The dataset used only took Javanese Ginseng, Urang-Aring, Moringa, Spinach Duri, and Dadap Serep, with each subject having 100 pictures of medicinal plants in each class. In each subject, 80 images will become a dataset. The training and the remaining 20 images will be used for the testing. Before the training process, the sample needs to undergo pre-processing.

2. Proposed Classification Model

   After collecting the plant leaves dataset at the initial stage, we continue to the next stage to pre-processing before feeding to the training. In this training process, the input image data will go through a training process using the Convolutional Neural Network method, which will form a model that will later be tested for its performance.

   We use the training dataset to get better boundary conditions which could be used to determine each target class. Once the boundary conditions are determined, the next task is to predict the target class. The whole process is known as classification. A classification model attempts to draw some conclusions from observed values. Given dataset inputs, a classification model will try to predict the value of the outcomes.

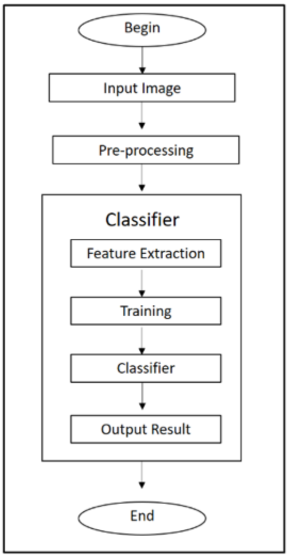


Fig 6. Leaf types classification process

At this stage, the data that has gone through the training process will be classified. This process produces a level of accuracy related to the match between the input data and the existing database/data model. Leaf pattern recognition usually follows several steps. The most challenging part of this study is to extract distinctive features of leaves for plant species recognition.

In this study, Grayscale's conversion of the image into geometrical data is implemented to optimize images' contrast and intensity. Later, the thresholding process creates a binary image from the Gray scaled image to translate the image's value to its closest threshold, therefore having either one of two possible values for each pixel. Different types of noises, such as grains, and holes, could affect digital images. Therefore erosion and dilation are a series of operations implemented to remove the background noises. The images are considered homogenous if they do not exhibit substantial differences between one another in terms of contrast stretching.

These images, when shown in histogram representation, exhibit very narrow peaks. Inhomogeneity is caused by the lack of uniform lighting upon the image. The image is normalized to stretch the limited range to a more dynamic range. The binary images from the process are inverted during threshold conversion to convert the background into black. Suzuki algorithm can be utilized to extract the contours of images and further refine the contours with small lengths regarding its most prominent contour.

## 5. Result & Analysis

In this part, we present our CNN architecture's testing result to measure the layer's effect on network performance. At this first phase, we calculate accuracy as a metric applied to leaf classification tasks. Then, we obtain a loss score as a distance between the true values of the problem and the values predicted by the model. It describes just what percentage of your test data are classified correctly. We conduct the training and validating process by using 28x28 pixel images with 5 and 7 layers. Fig. 7 depicts the training and validating result in leaf classification using 5-layer CNN architecture.

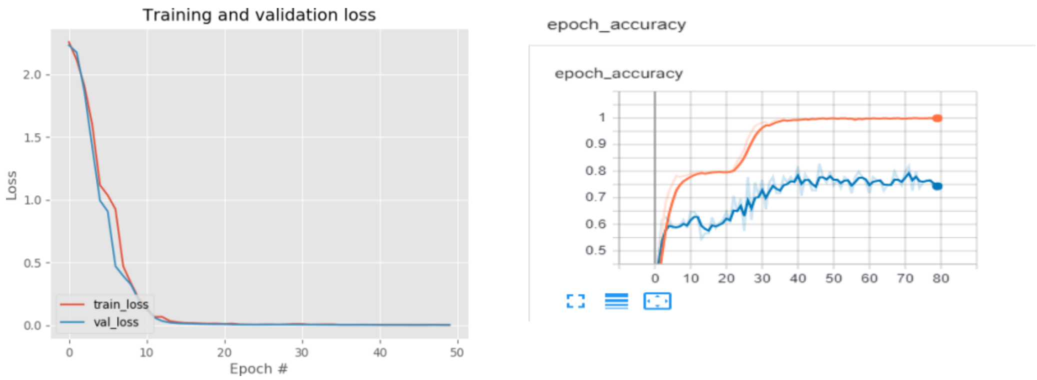


Fig. 7. Training and Validation Loss with five layers

This study also presents training and validating results using different layers (7 layers) in the same CNN concept. The proposed topology can achieve the optimal accuracy level with data validation at 80% based on the experiment. Fig. 8 depicts the training result using seven layers in CNN architecture.


Fig. 8 Training and Validation Loss system with seven layers

Based on Fig. 8 depict training results using seven layers, the optimal level of validation data accuracy reaches 100% at epoch 4. In this study, if we put few layers, the training process does not take a long time. The neural network topology applies more layers to test learning performance. However, it causes a bit more training time. We find that the more learning with more layers can harvest, the better the leaf classification result.

To convince our model performance, we also calculate the F1-score to express the harmonic mean of precision and recall. The scores corresponding to every class will tell us the classifier's accuracy in classifying the data points in that particular class compared to all other classes. The support is the number of samples of the actual response in that class of this case. Fig.9 depicts the calculation result of Precision, Recall, F1-Score in the leaf classification problem.

```
              precision    recall  f1-score   support

   bayamduri       0.22      0.24      0.23        80
 dadap serep       0.20      0.16      0.18        80
gingsengjawa       0.16      0.26      0.20        80
       kelor       0.18      0.19      0.18        81
 urang-aring       0.22      0.10      0.14        80

    accuracy                           0.19       401
   macro avg       0.20      0.19      0.19       401
weighted avg       0.20      0.19      0.19       401

Confusion Matrix
<matplotlib.axes._subplots.AxesSubplot at 0x7f99c7d66550>
```

Fig.9 Classification report

In this part, we present the F1 score to seek a balance between Precision and Recall. We calculate F1-Score when accuracy can be largely contributed by many True Negatives which in leaf classification. This leaf classification problem needs a balance score of Precision and Recall. Thus F1 score might be a better measure to use to seek a balance between them.

## 6. Conclusion

Implementation of Deep Learning in agriculture has increased enormously in the last decade, including their use to classify different plant leaves. More recently, many deep learning-based approaches for plant leaf stress identification have been proposed in the literature, but there are only a few partial efforts to summarize various contributions. In this paper, we train a model with 500 image data to classify leaf types. Based on the experiment result, we obtain an accuracy was 0.86, the precision of 0.22, f-1 score of 0.23, while recall was 0.2375. In this study, the accuracy is 0.86, precision 0.22, f-1 score 0.23, while recall is 0.2375. Based on experimental results, we can conclude that the implementation of CNN architecture for classifying leaf types can help develop deep learning in agriculture research. We hope that this research can help the public in recognizing five types of medicinal plants.


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# References


[1] Abhirawa H., Jondri, & Arifianto A. (2017). Face Recognition Using Convolutional Neural Network. e- Proceeding of Engineering: Vol. 4, No.3 December, Page 4907

[2] Asriny, Dhiya Mahdi. *Implementation of Deep Learning Using Convolutional Neural Network for Classification of Citrus Images*. Diss. Islamic University of Indonesia, 2019.

[3] H. J. Jie and P. Wanda, “RunPool: A Dynamic Pooling Layer for Convolution Neural Network,” vol. 13, no. 1, pp. 66–76, 2020.

[4] Diqi, Mohammad; Muhdalifah, Mujastia. Design and Building Javanese Script Classification in The State Museum of Sonobudoyo Yogyakarta. International Journal of Informatics and Computation, [Sl], v. 1, n. 2, p. 35-45, Feb. 2020. ISSN 2714-5263.

[5] P. Wanda and H. J. Jie “DeepProfile: Finding fake profile in online social network using dynamic CNN,” J. Inf. Secur. Appl., Vol.52, June 2020

[6] A., Sutskever I., & Hinton GE (2012). ImageNet Classification with Deep Convolutional Neural Networks. In Proceedings of NIPS.

[7] Kusumaningrum, Tutut Furi. "Implementation of Convolution Neural Network (CNN) for Classification of Mushroom Consumption in Indonesia Using Hard." (2018).

[8] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning is applied to document recognition. Proceedings of the IEEE. 86 (11): 2278- 232.

[9] Ludwig J., (2013). Image Convolution.

[10] Wijaya, Nurhadi. Evaluation of Naïve Bayes and Chi-Square performance for Classification of Occupancy House. International Journal of Informatics and Computation, [Sl], v. 1, n. 2, p. 46-54, Feb. 2020. ISSN 2714-5263

[11] O'Shea K. & Nash R. (2015). An Introduction to Convolutional Neural Networks. arXiv: 1511.08458v2 [cs.NE] December 2.

[12] P, I Wayan Suartika Eka (2016) Image Classification Using Convolutional Neural Network (Cnn) at Caltech 101. Undergraduate thesis, Sepuluh Nopember Institute of Technology.

[13] Ravi, S. & Nayeem, S. (2013). A Study on Face Recognition Technique based on Eigenface. FCS Foundation of Computer Science, New York, USA Volumes 5– No.4. International Journal of Applied Information Systems (IJAIS) - ISSN: 2249-0868.

[14] Zufar, M. & Setiyono B. (2016). CNN for Real-Time Facial Recognition. JOURNAL OF SCIENCE AND ARTS ITS Vol. 5 No. 2. A-72.

[15] P. Wanda, Marselina Endah H, Huang J. Jie, “DeepOSN: Bringing deep learning as malicious detection scheme in online social network” IAES International Journal of Artificial Intelligence (IJ-AI), Vol:9, No:1, 2020.

[16] Wanda, P. and H. Jie. “DeepSentiment : Finding Malicious Sentiment in Online Social Network based on Dynamic Deep Learning.”, 2019.

[17] Liu, J., ShuQin Yang, Yunling Cheng and Zhishuang Song. “Plant Leaf Classification Based on Deep Learning.” 2018 Chinese Automation Congress (CAC), 3165-3169, 2018.

[18] S. K. Noon, M. Amjad, M. A. Qureshi, and A. Mannan, “Use of deep learning techniques for identification of plant leaf stresses: A review,” Sustain. Comput. Informatics Syst., vol. 28, p. 100443, 2020.

[19] Lestari, Sri et al. “Measurement of maximum value of dental radiograph to predict the bone mineral density.” 2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), 1-4, 2017.