A Comprehensive Introduction to Convolutional Neural Networks: A Case Study for Leaf Image Classification

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Abstract

Most of the today's new and innovative artificial intelligence applications are based on the artificial neural types of networks to capture, interpret and analyze various kind of data. A Convolutional Neural Network is a type of artificial neural network used primarily for image recognition and processing due to its ability to patterns in images. A deep learning algorithm is adopted to classify images and detect objects in an image with the neural network. In this study, Convolutional Neural Networks Model is used for performing automatic feature extraction on binary classification with leaf image dataset. It works by investigating and processing large amount of data in a grid format and then extracting important features for classification detection. It is discussed in this study the use of deep learning techniques to automatically detect diseases in plants. Further, it emphasizes the working principles of Convolutional Neural Networks. Hence, the study intends to present a comprehensive way of the modeling techniques. Moreover, the study seeks fundamentals on deep learning mechanisms which is useful to beginners on the area of artificial intelligence. Therefore, this study is carried out intentionally as a case study which emphasizes the automatic leaf image binary classification. The findings of the present study showed 81.3% of the maximum accuracy of the modeling.

Keywords: Artificial Intelligence, Binary Classification, Convolutional Neural Networks, Deep Learning, Disease Identification, Feature Extraction

I. INTRODUCTION

The Convolutional Neural Network (CNN) models can be used to determine diseases in plants based on leaf images, since CNNs have performed higher accuracy results in the machine vision (Barbedo, J.G.A., 2016). It is a very difficult task of determining healthiness of plant leaves based on image, as it is difficult to extract leaf features exactly. It also affects the capturing of environment. Healthiness of leaf leads to the healthiness of its plant (Wallelign, Polceanu and Buche, 2018). There is a continuous development in predicting plant diagnosis with digital image processing and computer vision techniques. In the proposed approach, there are two phases which follows firstly reviewing the existing literatures of necessities on developing framework of CNN models and then illustrating the model with a leaf image dataset. The study investigated and analyzed the most recent methods for recognizing and practicing of an algorithm with CNN model on classifying leaf categories.

There may be an error visually when identifying diseases by human. The detecting and classifying diseases which is the great importance in a timely manner (Barbedo, 2016). The classification of data is graded by employing Fuzzy Logic to determine a particular class. In this analysis, a high computational effort is required for such an image processing-based method but some initiatives can reduce the computational cost Hassan *et al.*,2021. We also investigated the role of image analysis in automated process and recognition, regardless the object of the images.

The present study aims to develop a profile of CNN classification algorithm tailored for image classification techniques. In addition, the secondary objectives are to determine the set of employed features and the framework for the image restoration and to evaluate the influencing characteristics of the images. Making it more difficult for an automatic algorithm to perform a meaningful analysis on a ground level, a comprehensive view of the modeling techniques has been incorporated in this study.

It is important to notify since the identification of plant diseases is considered as a timely needed study for taking wise decisions on protecting the plant and its quality, the automated disease identification may help in finding a remedy at the earliest stage to control the damages in plant.

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Deep learning seems to be a better option to resolve this challenge (Zhang, Zhang and Lv, 2022). Most of the methods are only capable for discriminating particular type of diseases. The present study intended to learn how CNN classification algorithm determines a crop healthy or not.

II. LITERATURE REVIEW

Wallelign, Polceanu, and Buche in 2018 described the feasibility of CNN for plant disease classification in leaf images taken under the natural environment. The model was designed based on the LeNet architecture to perform the soybean plant disease classification. A large number of samples containing leaf images of four classes, including the healthy leaf images, were obtained from the Plant Village database. The images were taken under uncontrolled environment. The classification accuracy of 99.32% is achieved through this implemented model which shows clearly that CNN can extract important features and classify plant diseases from images taken in the natural environment.

Barbedo in 2016 used a method for disease identification, based on color transformations, color histograms and a pairwise-based classification system. Its performance was tested using a large database containing images of symptoms belonging to 82 different biotic and abiotic stresses, affecting the leaves of 12 different plant species. By analyzing the above literatures, present study intend to perform CNN analysis with binary classification on leaf disease identification because CNNs are used in a variety of computer vision tasks due to their flexibility.

III. MATERIALS AND METHODS

A. Materials

Firstly, the digital images were acquired from the environment by using smart phone cameras. Figure 01 shows some sample images from dataset.

Then the image-processing techniques were applied to the acquired images to extract useful features that are necessary for further analysis. After that, several analytical discriminating techniques were applied to classify the images according to the specific problem in hand. Figure 02 depicts the basic procedure of the proposed vision-based detection algorithm in this research (Zhang *et al.*,2015).

Figure 01: Sample Images

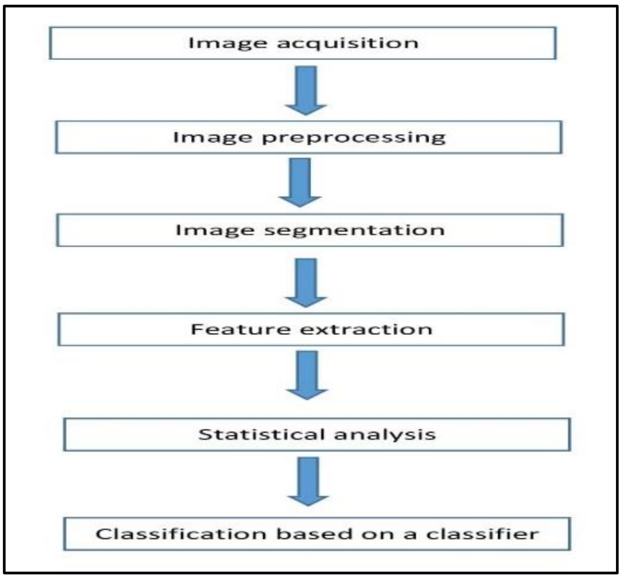

Figure 02: Overall Framework of the Study

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B. Methods

Leaf image data were collected from different home gardens in various weather conditions, at different angles, and daylight hours with an inconsistent background mimicking practical situations (Barbedo, J.G.A., 2016). The Table 01 shows the sample collections of leaf images.

The dataset contains over 200 images (Table 01), the multiple plant types and lesion types and the staggering differences in the images make it difficult to perform feature extraction. Nevertheless, deep learning, particularly the CNN model, necessitate numerous data to undertake the training process (Walleligm, Polceanu and Buche, 2018). Therefore, it is necessary to adopt data augmentation on the dataset before performing feature extraction. The sample images after data augmentation is shown in Figure 03.

IV. CASE STUDY

In this section, it is considered the problem of recognizing several sources to illustrate the application of CNN. It consists of four main layers: convolutional layer, pooling layer, activation function layer and fully connected layer (Wallelign, Polceanu and Buche, 2018). This model is developed in Python language by using the deep learning libraries: NumPy, and Keras. The experimental environment is Jupyter Notebook, with Python 3.7. Researchers used a batch size of 32 that is a hyper-parameter to adjust in deep learning. The sample data generation for training is shown Figure 04.

Table 01: Details of Leaf Image Dataset

Type	**Leaf Image**	
	Class	**No. of Images**
Common	C	66
Damaged	D	74
Good	G	69

Source: Developed by Researchers

Figure 03: Sample Images After Augmentation

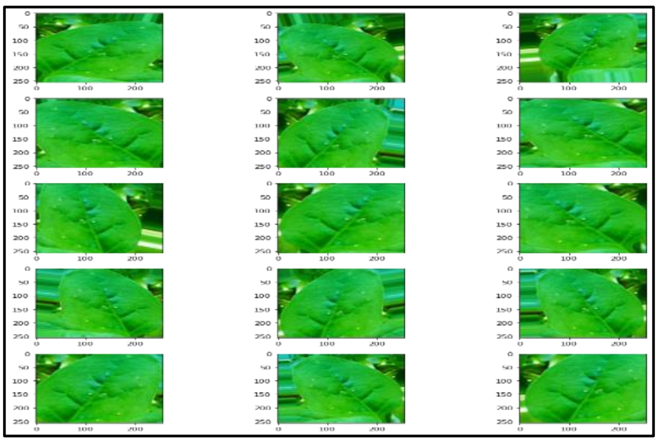

Figure 04: Example of Validated Images

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V. RESULTS AND DISCUSSION

This section presents the results individualized for each plant species, which are labeled in alphabetical order without considering the original plant species categories. It is found from the validation that the algorithm provided reasonably good estimates in 80% of the cases. Table 02 shows that the comparison of modeling approach with related studies. The breakdown list of extracted output is shown in Table 03 and The proposed algorithm for training accuracy versus validation accuracy is shown in Figure 05.

Table 02: Results Comparisons with Related Studies

Reference	**Year**	**Used Architecture**	**Limitations**
Barbedo	2016	LeNet	Limited effectiveness for sequential data.
Hassan *et al.*	2021	VGG-16, VGG-19,	Needs large amount of labeled data.
Wallelign et al.	2018	VGG-16, VGG-19, ResNet, InceptionV3	Needs large amount of labeled data.
Zhang *et al.*	2022	ResNet-50, SE-ResNet-50	High computational requirements.
Zhang *et al.*	2015	AlexNet Fuzzy-SVM, CNN, R–CN	No real-time web-based deployment
Our proposed approach	-	CNN	Single model applied, No deployment

Table 03: Model Fit Generator

22/22 [======] - 20s 932ms/step - loss: 0.6815 - a ccuracy: 0.6509 - val_loss: 1.0714 - val_accuracy: 0.6400 - lr: 1.0000e-05
Epoch 2/30
22/22 [======] - 20s 910ms/step - loss: 0.7877 - a ccuracy: 0.6132 - val_loss: 1.0674 - val_accuracy: 0.6000 - lr: 1.0000e-05
Epoch 3/30
22/22 [======]- 20s 912ms/step - loss: 0.7242 - ac curacy: 0.6887 - val_loss: 0.9475 - val_accuracy: 0. 6400 - lr: 1.0000e-05
Epoch 5/30
22/22 [======]- 20s 907ms/step - loss: 0.7424 - ac curacy: 0.6226 - val_loss: 1.0236 - val_accuracy: 0. 5600 - lr: 1.0000e-05

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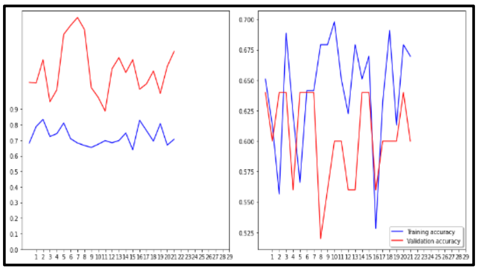

Figure 05: The Model Training Accuracy Versus Validation accuracy

VI. CONCLUSION

The present study provided guidelines and procedures to follow in order to maximize the potential of CNNs deployed in real-world applications. Accordingly, the overall accuracy of the algorithm for leaf image classification was 81.3%. The binary classification applied intentionally in order to make quick decision. Based on the results, controlling the trade-off between accuracy and training speed, it is recommended that slowly increase the number of kernels and add new layers would be a successful process. Findings from this research can be extended in future studies by incorporating more practical implications for real time classification tasks in massive and small level in the field of agriculture.

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