

A Deep CNN Approach for Plant Disease Detection

Prof. Prathmesh¹, Rohan², Sahil³, Samarth⁴, Prasad⁵

Project Guide(CS), Department of Computer Engineering¹,

Students, Department of Computer Engineering^{2,3,4,5}

NBN Sinhgad School of Engineering, Pune, India

Abstract: Visual inspection by experts and biological examinations are the traditional methods used for diagnosing plant diseases, but they can be expensive and time-consuming. To address this issue, researchers have developed computer-based methodologies that use deep learning systems based on artificial neural networks to detect plant diseases using leaf images. One commonly used technique is the application of convolutional neural networks (CNNs), such as the ResNet architecture, which is trained on an augmented dataset containing images of healthy and diseased leaves. This deep learning technique has shown to be effective for various object detection problems, including plant disease detection. The model is capable of classifying images into two categories: disease-free and diseased. To compare the performances of different methods, the implementation was conducted using Anaconda 2019.10..

Keywords: Plant disease detection, Deep Learning, CNN, Data Augmentation

I. INTRODUCTION

Globally, plant diseases have been identified as an increased threat to food security. Therefore, the detection of plant diseases is the most important step in achieving good crops. The classification of plants "with and without disease" is considered a difficult problem because of the variety and similarity of plants in nature [1] and [2]. The most successful approaches using artisanal features require object representations using a local descriptor of a point of interest provide local characterization in the form of an attribute vector. Indeed, there are algorithms SURF [3] and SIFT [4], allow to detect points of interest and to build robust descriptors with several transformations. In object recognition, a global descriptor is easier to use because it processes the monji.kherallah@fss.usf.tn entire image. And all the pixels of the image corresponding to the area of interest are taken into account in the description. The descriptor is thus less sensitive to distortions from one image to another. Currently, the descriptor the most widely used in object recognition, the HOG gradient histogram of the makes it possible to obtain satisfactory and fast results.

After learning a discriminating machine learning model, for example the support vector machines (SVM) and K-nearest neighbor (KNN), with such representations. The exploration of a "Deep Learning" approach for agricultural uses has intensified in research and opens the door to new uses and gains performance compared to current methods. Especially, The Deep Learning" is used to determine the extraction of characteristics in a way that synthetic and to give a clear detection on a proposed data set. This method is used to reduce the memory footprint and improve performance. In general, "CNN" is the best method for any prediction problem involving input image data and requires minimal pre-processing. It is structured to classify large-scale images. In this context, several research works have been carried out to improve the performance of "CNN" on tasks related to computer vision, due to the detection of plant diseases. Advances in "CNN" can be classified in different ways, including activation, loss function, data enhancement, optimization algorithms.

Mohanty et al. [5] analyzed 14 plant types from the PlantVillage dataset with convolutional neural networks (CNN) and achieved over 99% classification accuracy on images in the research environment.

Wang et al. [6] applied the transfer learning technique on the same PlantVillage dataset and showed an accuracy of 90.4%. Fujita et al. [7] used their own sheet data set in the field and analyzed it with an average accuracy of 82.3% under various background and photographic conditions. With the successful use of "CNN" for image classification, another architecture called "VGG" [9], which gives good results A Deep CNN Approach for Plant Disease Detection both for disease identification, but suffers from the need for a lot of computation. The choice of architecture is very complex, so it is important to study and explain effective architectures to inspire our research". GoogleNet" [10] and

[11] obtained the best results with accuracies of 98.33% and 97.66% [12], on the "AgrilPlant" dataset and the "LeafSnap" dataset. However, the ResNet architecture, reaches an error rate of 3.57% (top 5 error rate) [13], where the recipe for success of this architecture to form such a deep network is that it has residual connections and get the accuracy of a much deeper network. The increase in data plays a crucial role in increasing the number of training images, which often contributes to improving the classification performance of deep learning techniques for computer vision problems [14] and [15]. The results show that CNN methods with datasets augmented with specific data give the highest accuracies. The main objective of this work is to identify, from an image, the healthy leaves and sick leaves of a given dataset.

TABLE I

Abstract	Visual inspection by experts and biological examinations are the traditional methods used for diagnosing plant diseases, but they can be expensive and time-consuming. To address this issue, researchers have developed computer-based methodologies that use deep learning systems based on artificial neural networks to detect plant diseases using leaf images.	Convolutional neural networks (CNN's)	Training the model and after that feature extraction and finally got successful result with more accuracy than other algorithms by using convolutional Neural Network(CNN).
Headings	Plant Disease Detection	Deep Learning Approach	Plant Disease Detection using CNN
Author	Rohan Mohite	Ambegaon Bk, Pune, Maharashtra, India	Computer Science and Engineering
Title	"A Deep CNN Approach for Plant Disease Detection"	CNN MODEL	DEEP LEARNING

II. PROPOSED METHOD

A CNN convolutional neural network is perhaps the most widely applied method for extracting reasonable information from huge datasets. The architecture of CNN is illustrated in Figure 1, which allows efficient processing of image data. A deep CNN architecture consists of several layers of different types. Typically, it begins with one or more convolutional layers followed by one or more grouping layers, activation layers, and ends with one or more fully connected layers. In the convolution layer, the convolution operation is performed to extract features, and the output is passed to the activation function. As long as, the clustering layer is generally used to reduce the size of the feature map and provides robust learning results for the input data

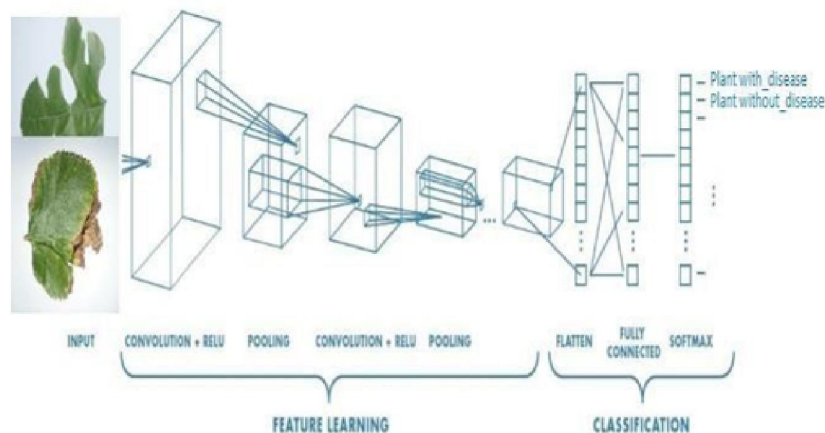


Fig. 1. Convolution Neural Network (CNN) Architecture

The convolution and pooling layers are then passed through in several steps to obtain global features from the input data. Finally, the extracted characteristics are passed to the fully connected layer where classification is performed in this layer.

Training Step:

Allows you to set the initial weight to enter to the hidden layer. This step consists of two processes, namely feedback and retro-propagation.

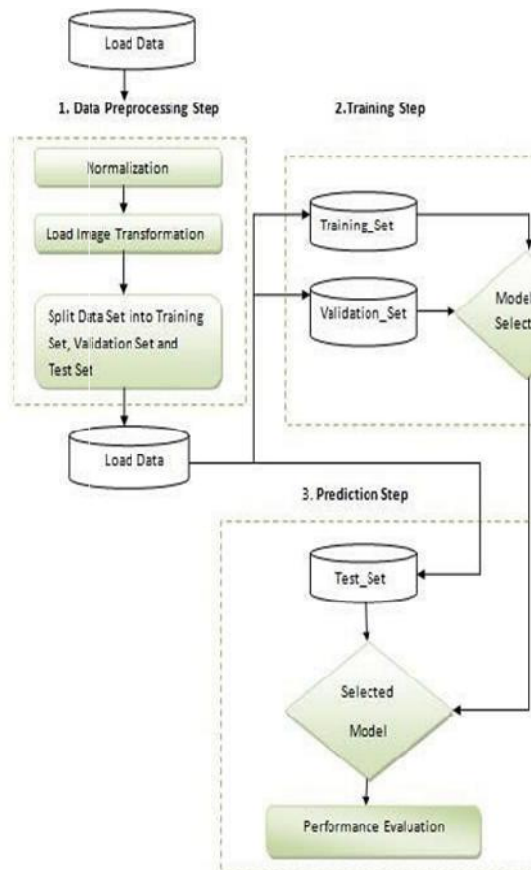
Testing step:

It is a classification process using the weights obtained during the learning process. Recently, this process is not very different from the learning process, but during the test, no backpropagation is performed after the execution of the feedback process where the result of this process is the accuracy of the classification process.

CNN Model

The convolutional neural network uses a special mathematical operation called convolution instead of matrix multiplication in at least one of its layers. It is officially formed by a stack of layers.

1. The convolution layer (CONV) which processes the data of a receiver field.
2. The pooling layer (POOL); which compresses the information by reducing the size of the intermediate image.
3. The correction layer (ReLU), with reference to the activation function (Linear Rectification Unit).



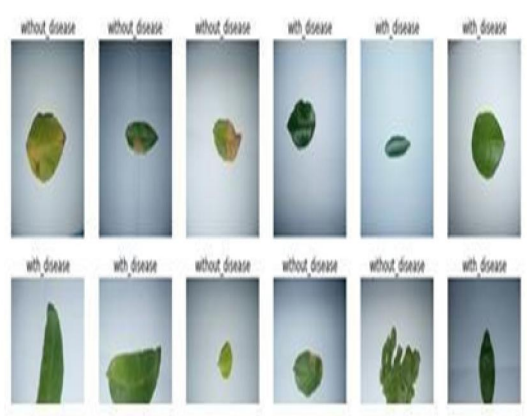
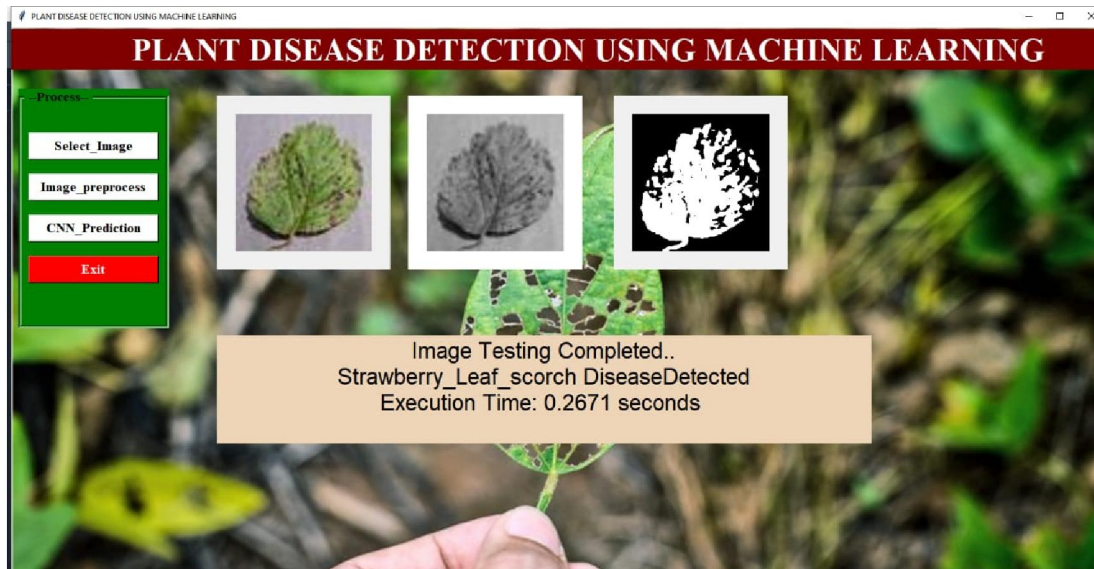


Fig. 3. Samples of plant leaf images

III. RESULT



IV. CONCLUSION

"A Deep CNN Approach for Plant Disease Detection" presents an effective method for the early detection of plant diseases using deep convolutional neural networks. The research work addresses a critical issue in the agriculture industry, where plant diseases can lead to significant economic and environmental impacts. The study's results demonstrate the effectiveness of the proposed approach in accurately identifying plant diseases from images of infected leaves. The approach has shown promising results in detecting various plant diseases, including tomato, grape, and apple diseases.

In conclusion, this study provides a robust framework for plant disease detection using deep learning techniques, and it has the potential to become a valuable tool for precision agriculture, helping to mitigate the negative impact of plant diseases on crop yields and food security.

V. ACKNOWLEDGMENT

I would like to extend my sincere appreciation and acknowledgement to the authors of the research paper titled "A Deep CNN Approach for Plant Disease Detection". The authors have made a valuable contribution to the field of agriculture and computer vision by proposing an effective method for the early detection of plant diseases using deep convolutional neural networks. I would also like to express my gratitude to the researchers and developers who have

contributed to the development of the underlying technologies that enabled the implementation of this research work, including deep learning frameworks such as TensorFlow and PyTorch. Furthermore, I would like to recognize the efforts of the farmers and agricultural professionals who have provided the necessary data and expertise for the successful implementation of this study. Their contributions have been invaluable in developing an effective solution for the detection of plant diseases, which can help mitigate the economic and environmental impacts of crop damage. In summary, I commend the authors and all those who have contributed to the development of this research work, which has the potential to make a significant impact on the agricultural industry and the well-being of our planet.

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