Advanced Plant Disease Detection Using Neural Network

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Abstract- *The latest generation of convolutional neural networks (CNNs) has achieved impressive results in the field of image classification. This paper is concerned with a new approach to the development of plant disease recognition model, based on leaf image classification, by the use of deep convolutional networks. Novel way of training and the methodology used facilitate a quick and easy system implementation in practice. The developed model is able to recognize different types of plant diseases out of healthy leaves, with the ability to distinguish plant leaves from their surroundings. All essential steps required for implementing this disease recognition model are fully described throughout the project starting from gathering images in order to create a database and neural network is used to perform disease prediction.*

Keywords- Convolutional neural network, Image classification, plant disease detection.

I. INTRODUCTION

Early plant disease detection plays a significant role in efficient crop yield. Plant diseases like black measles, black rot, bacterial spot, etc. affect the growth, crop quality of plants and economic impacts in the agriculture industry. To avoid the impact of these diseases, expensive approaches and the use of pesticides are some solutions the farmers usually implement. The use of chemical means damages the plant and the surrounding environment. In addition, this kind of approach intensifies the cost of production and major monetary loss to farmers. Early discovery of diseases as they occur is the most important period for efficient disease management. Manual disease detection through human experts to identify and recognize plant diseases is a usual practice in agriculture [1]. With the improvements in technology, automatic detection of plant diseases from raw images is possible through computer vision and artificial intelligence researches [2]. In this study, the researchers were able to investigate plant diseases and pest's infestation that affects the leaves of the plants. Image processing techniques are now commonly employed in agriculture and it is applied for the detection and recognition of weeds [3], fruit- grading [4], identifying and calculating disease infestations of plants [5], and plant genomics [6]. Currently, the introduction of deep learning methods turns out to be popular [7]. Deep learning is the advanced methods of machine learning that uses neural networks that works like the human brain [8]. Traditional methods involve the use of semantic features as the classification method [9]. LeChun et al. describes deep learning as a neural network learning process and one feature of deep learning is that it can automatically obtain features through image patterns [10]. A convolutional neural network (CNN) is a deep learning model that is widely used in image processing. The work of Lee et al. [11] presents a hybrid model to obtain characteristics of leaves using CNN and classify the extracted features of leaves. The study of Ferentinos, K.P. uses simple and infected plant leaf images to detect plant diseases using pre-trained CNN model [12]. Durmus et al work on the detection of diseases of the tomato leaves using AlexNet and SqueezeNet pre-trained CNN architectures [13]. While Atabay et al. [14] contributed a new CNN architecture to do disease classification and identification. The methodology in the study involves three key stages: acquisition of data, pre-processing of data and image classification. The study utilized dataset from Plant village dataset[15] that contains plant varieties of apple, corn, grapes, potato, sugarcane, and tomato. There are 11 types of plant diseases identified in the study including healthy images of identified plants. Image pre-processing involves re-sized images and enhancement before supplying it for the classification model.

II. CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Network Deep learning is a subsection of Artificial Intelligence and machine learning that uses artificial neural networks (ANN). Training the deep learning models divides the feature extraction and extracts its features for classification. There are several applications of deep learning which include computer vision, image classification, restoration, speech, video analysis, etc. A convolutional neural network with nominal process can simply detect and categorize. It is efficient in evaluating graphical images and extracts the essential features through its multi-layered structure. As shown in Fig. 1, the CNN involves four layers, that is: input image, convolutional layer and pooling layer, fully connected layers, and output.

Fig1. Illustration of Convolutional Neural Network Architecture

A. Convolutional Layer

Convolutional layers store the output of the kernels from the previous layer which consists of weights and biases to be learned. The generated kernels that represent the data without an error is the point of the optimization function. In this layer, a sequence of mathematical processes is done to extract the feature map of the input image [16]. Fig. 2 exhibits the operation of the convolution layer for a 5x5 image input and a result is a 3x3 filter that reduced to a smaller size [17]. Also, the figure shows the shifting of filter starting from the upper left corner of the input image. The values for each step are then multiplied by the values of the filter and the added values are the result. A new matrix with the reduced size is formed from the input image.

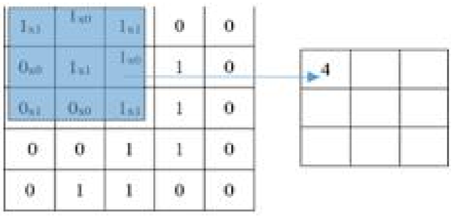


Fig. 2 5x5 input and 3x3 filter operation of convolution layer.

B. Pooling Layer

This layer reduces overfitting and lowers the neuron size for the downsampling layer. Fig. 3 illustrates an example of the pooling operation. This layer reduces the feature map size, reduce parameter numbers, training-time, computation rate and controls overfitting [20]. Overfitting is defined by a model by achieving 100% on the training dataset and 50% on test data. ReLU and max pooling were utilized to lower feature map dimensions [21].

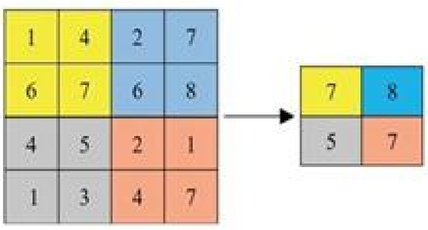


Fig.3.Pooling operation

C. Activation Layer

Utilizes a non-linear ReLU (Rectified Linear Unit) activation layer in every convolution layer. The application of dropout layers to prevent overfitting is also applied in this layer.

D. Fully Connected Layer

This layer is used to analyze the class probabilities and the output is the input of the classifier. Softmax classifier is the well-known input classifier and recognition and classification of diseases are applied in this layer.

III. METHODOLOGY

A block diagram presented in Fig. 4 shows the Input Dataset, Image pre-processing, data augmentation, neural network training.

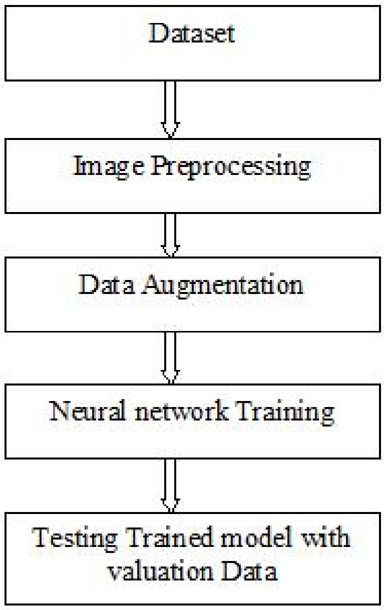


Fig. 4 Plant leaf detection and disease recognition methodology

A. Input Dataset

Appropriate datasets are required at all stagesof object recognition research, starting from training phase to evaluating the performance of recognition algorithms. All the images collected for the dataset were downloaded from the Internet, searched by disease and plant name on various sources in different languages, such as Latin, English, German, Serbian, and Hungarian. Images in the dataset were grouped into fifteen different classes. Thirteen classes represented plant diseases which could be visually determined from leaves.

In order to distinguish healthy leaves from diseased ones, one more class was added in the dataset. It contains only images of healthy leaves. An extra class in the dataset with background images was beneficial to get more accurate classification. Thus, deep neural network could be trained to differentiate the leaves from the surrounding. The background images were taken from the Stanford background dataset. In this stage, all duplicated images taken from different sources were removed by developed python script applying the comparing procedure. The script removed the duplicates by comparing the images' metadata: name, size, and the date. After the automated removal, images were assessed by human experts in much iteration.

B. Image Preprocessing

Images downloaded from the Internet were in various formats along with different resolutions and quality. In order to get better feature extraction final images intended to be used as dataset for deep neural network classifier were preprocessed in order to gain consistency. Furthermore, procedure of image preprocessing involved cropping of all the images manually, making the square around the leaves, in order to highlight the region of interest (plant leaves). During the phase of collecting the images for the dataset, images with smaller resolution and dimension less than 500 px were not considered as valid images for the dataset. In addition, only the images where the region of interest was in higher resolution were marked as eligible candidates for the dataset. In that way, it was ensured that images contain all the needed information for feature learning. Images used for the dataset were image resized to 256×256 to reduce the time of training, which was automatically computed by written script in Python, using the OpenCV framework.

C. Augmentation process

The main purpose of applying augmentation is to increase the dataset and introduce slight distortion to the images which helps in reducing over fitting during the training stage. In machine learning, as well as in statistics, over fitting appears when a statistical model describes random noise or error rather than underlying relationship .The image augmentation contained one of several transformation techniques including affine transformation, perspective transformation, and simple image rotations. Affine transformations were applied to express translations and rotations (linear transformations and vector addition, resp.) where all parallel lines in the original

image are still parallel in the output image. To find a transformation matrix, three points from the original image were needed as well as their corresponding locations in the output image. For perspective transformation, a 3×3 transformation matrix was required. Straight lines would remain straight even after the transformation. For the augmentation process, simple image rotations were applied, as well as rotations on the different axis by various degrees.

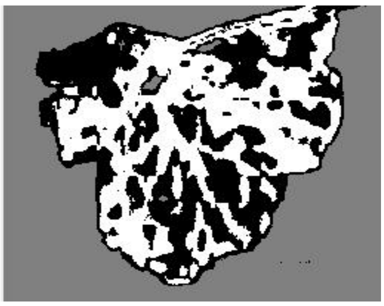
D. Neural Network Training

Training the deep convolutional neural network for making an image classification model from a dataset was proposed.

IV. RESULTS AND ANALYSIS

A 96.5% accuracy rate was achieved using 75 epochs during the training of the model. The model also achieved a maximum accuracy rate of 100% when testing random images of plant varieties and diseases. Fig. 6 shows of detection and recognition of a plant with 100% accuracy and it shows an accuracy rate of 100% recognition of healthy plant leaf on the left image . The input leaf image was labeled by cluster index is showed in fig 6. Then the fig 7. Described about the labeled image is being clustered into three type of clustered images. After the clustering image is now classified and showed the exact disease in fig 9.

Fig. 5 Input leaf image



Fig,6 Image Labeled by cluster index

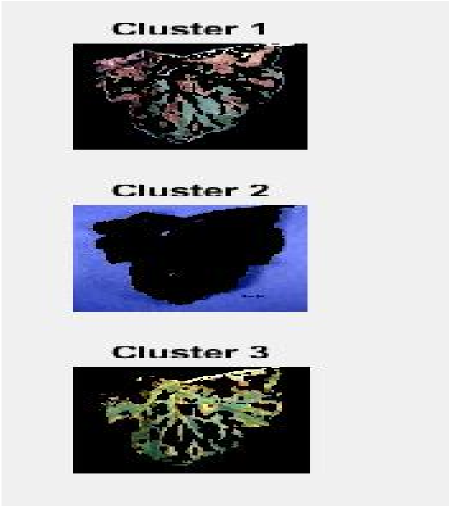


Fig .7 Cluster Selection

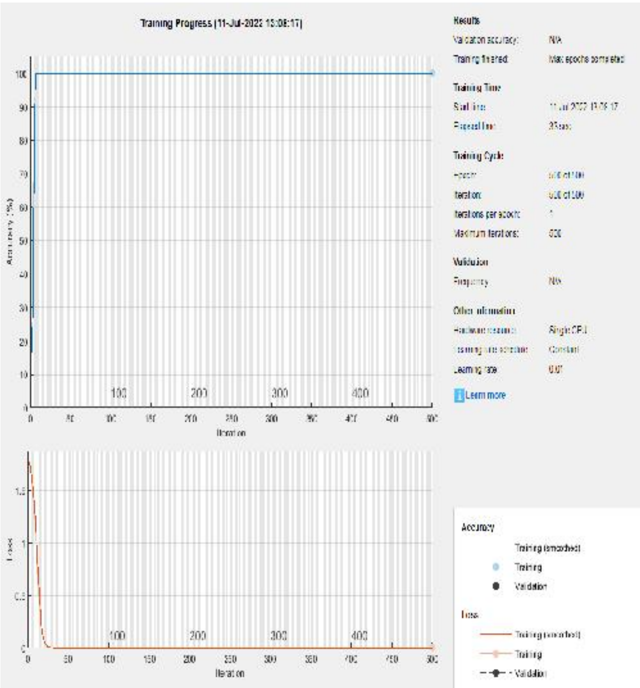


Fig.8 Training loss and accuracy

```
species_disease =

  1×1 cell array

    {'ANTHRANOSE'}
```

Fig .9 Disease detection

V. CONCLUSION

In this paper, a new approach of using deep learning method was explored in order to automatically classify and detect plant diseases from leaf images. The developed model was able to detect leaf presence and distinguish between healthy leaves and 13 different diseases, which can be visually diagnosed. The complete procedure was described, respectively, from collecting the images used for training and validation to image preprocessing and augmentation and finally the procedure of training the deep CNN and fine-tuning. Different tests were performed in order to check the performance of newly created model. With the achieved accuracy of 100%, the proposed model can assist farmers to detect and recognize plant diseases.

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