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Original Research

Recognition of Plant Diseases using DNN-Based Image Classification of Leaves

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Abstract

High performance has been reported on the current generation of CNNs in the image processing. From the perspective of this research, a wholly new approach of developing an identification model for plants from the surface photos by categorising with deep convolutional networks is adopted. In fact, the task of initiating the programme is rather easy in regards to a modern approach to teaching and learning. Thus, eliminating the need for manual intervention, the built model is able to differentiate between 13 types of plant illness and healthy leaves from the surrounding environment. As far as we can try to make an analysis, it can be concluded that this method of diagnosing plant diseases was launched for the first time. The report is detailed and covers every possible measure that may aptly be taken to introduce this disease diagnosis model and includes the process of compiling images that would be used to form a database approved by agricultural specialists. Caffe, a basic research system at Berkley Vision and Learning Center, carried out the comprehensive preparations for CNN. Scores achieved for the distinct class study based on the constructed model have been proved to be on average 91% to 98% trustworthy experimental results.

Keywords: DNN-Based Image, Classification of Leaves, Recognition of Plant Diseases

Introduction

A considerable portion of the production cost is directed at controlling plant diseases which pose a threat to the crop productivity and quality globally. Plant diseases are said to have an impact on the least =10% of the global food supply chain. On the farm, farmers employ plant pathologists to estimate the losses and to control diseases. Some of the common issues include; misdiagnosis and the use of excess pesticides [1]. Mentioned plants are very sensitive to diseases because they are open to the external environment, so the problems of disease prevention and control have always been acute. More often, a significant condition of disease control in plants is correctly identifying the illness because it can make practical protective actions [2]. Image segmentation, feature extraction and pattern recognition are the three stages which form the basis of pipelined processes that many of the recognition and diagnostic strategies use. Some kind of success along the lines of the recognition systems that implement pipelined procedures has been found. Nevertheless, there are two issues with these approaches. First of all, identification and isolation of seeming illness attributes is the critical step for such approaches. The right features should be selected, and concerning the feature-level representations of observable disease symptoms, these features should be extracted adequately. Second, there is a moderate level of intricacies in the methods deemed to execute subsequent to the pipelined procedures. The situation of having noise when practicing the process of capturing pictures of diseases in the field is nearly impossible to avoid as several factors including unequal illumination and debris field background will be present. This can cause degradation of the features' quality and affect the recognition results. Therefore, traditional methods pay significant effort to minimize interference in an effort to supply accurate results [1]. It can be concluded that the analysis of the current situation reveals the positive effects of such mechanisms that employ computer vision and other techniques for classifying plant diseases for some crops and illnesses. The accuracy of categorisation has further been enhanced mainly because of architectures based on deep Convolutional Neural Networks (CNNs) [3].

Various approaches to the automatic diagnosis of plant diseases are presented in the following paragraphs: A programme that is workable based on image processing of a plant, able to identify plant diseases without human interjection. The algorithm is quite simple to retrain to include more ailments and it is suggested to deal with various disorders. Owing to its histogram-based structure, it can be said that it is rather stable in terms of capturing photos in various situations. This would mean that there is a possibility of enhancing the situation and thus has the potential of producing better results. Today's medicine is overcrowded with disorders that manifest themselves in a vast number of signs. To address this issue, research has emerged on the application of such approaches as the integration of expert systems, image processing, and other methods of information acquisition. This approach is equally anticipated to have the potentiality of reforming most of the existing drawbacks experienced in today's clinical practice [5].

For the shaded and textured parts, the basic models are used along with system generative models where texts and faces are used. As a result of such interaction and collaboration, this method allows for determination of the input photographs of those different versions. This device creates a possibility for segmenting items, detecting faces and reading text in the urban complex. In this case, by explaining the lack of sunglasses and shadow occurrences, this particular system provided numerous examples where shaded model aided in the identification of faces and text. Thus, the face and text models improved the attractiveness of the segmentation quality. At the moment the methodology encompasses only the standard simulation of classes of objects. The reason for this limitation was to allow adequate identification of faces and text for the visually impaired individuals. Despite the effectiveness of this method being dependent on the type of objects, it is general to the most basic ones [6].

This detection approach depended on the cluster analysis of point counts, while the last classification utilized convolutional neural networks (CNNs). The idea of the proposed approach to evaluate clusters of points is based on the combined application of modelled fuzzy logic and graphics processing unit. To prove how effective the proposed detection and classification architecture is and to identify possible improvements for future developments, the presented architecture has been evaluated and compared with other works in the literature. Therefore, due to the findings detected and CNN, we were able to present appropriate item classifications. as for the accuracy rate we were able to get ; around 83% for face detection from the big database and 75% for other things like people, and only 55% for animals and around 80% for autos. From the above seventy results it was apparent that the suggested method held a lot of potential. anticipate correctly the chance of ARX differentials in order to avoid some of the problems that have been described above [7].

Thus the object in the chosen image is modeled using a Support Vector Machine. It should, therefore, be compatible with the object detection strategy that was suggested by employing the KPCA feature vector reduction and the detection by SVM classification system. An extraction technique that employs picture global descriptors. As a result of the descriptor and matching stages, along with normalization, in order to acquire features that are general to the image, a feature vector is generated. Specifically for full-image training a vector parameter utilizes KPCA as a means to minimize the dimensionality. The number of features is reduced for the classifier SVM and used a feature vector. In the later steps we input various test photos to the Classifier and check the results. To prove the inefficiency of classical methods in the identification of an object, the result is obtained using the SVM Classifier with the help of the Back Propagation Neural Network. There are works, which state that applying SVM classifier yields better results [8].

The Proposed Method:

A training phase and a classification phase make up the proposed system's framework. The pre-processing and features extraction modules are shared by both of these main phases, as illustrated in Figure (1).

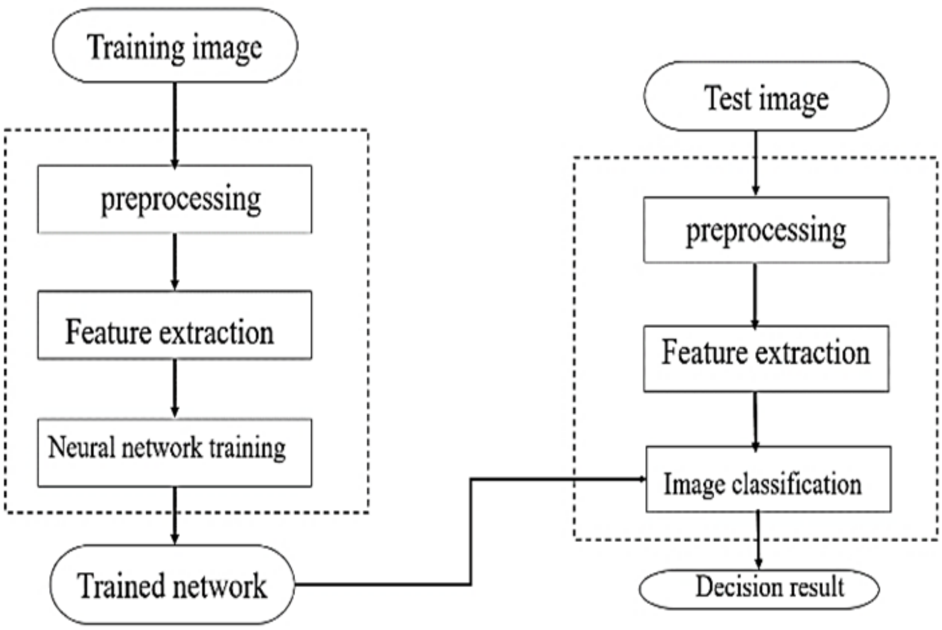


Figure 1. The framework of the proposed plant leaf diseases classification

Individual features vectors of each sample in the case of training samples are stored in a system database after pre-processing and features extraction steps during the training process. In the context of the classification process, the system is required to perform the matching of all the vectors contained in database with the feature vector of the input plant leaf image, and then deliver the file name to the dataset classifier. The suggested method applies a convectional neural network or CNN when it comes to the two matching and the decision process.

Machine Learning Approach

The two primary steps of the deep learning neural network approach to plant leaf diseases classification through images are:The two primary steps of the deep learning neural network approach to plant leaf diseases classification through images are:

- Many activities are associated with the enrolment phase of the process; pre-processing, localisation, extracted features, and tagged objects.
- The second stage which is matching also involves several processes such as pre-processing of features, localisation of features to be matched, extraction of features and the actual matching process. Figure 2 described the major actions of the proposed system and Fig 3 described the major actions of CNN

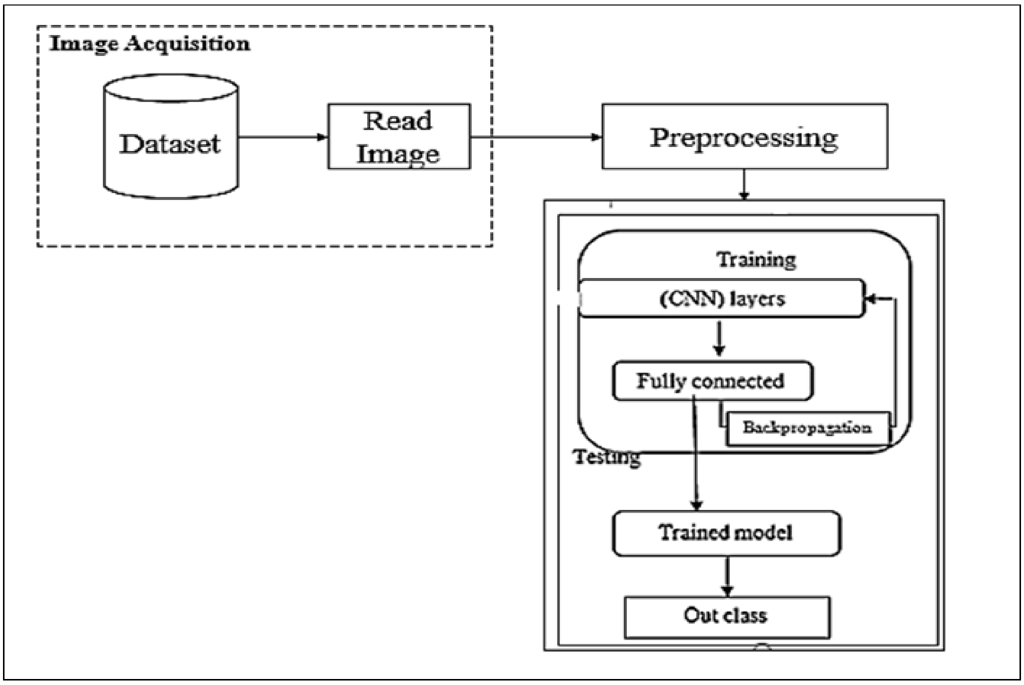


Figure 2. The main stages of the proposed system

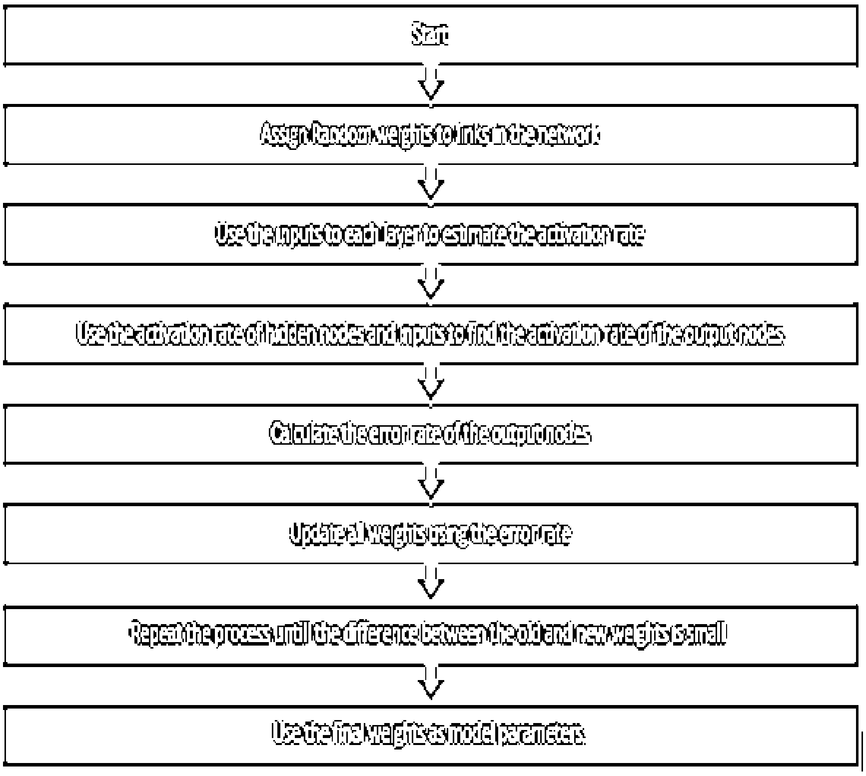


Figure 3. The main stages of CNN

Capturing Images

In general, when a vision system has a certain job to accomplish it always commences with picture acquisition. After an image is acquired, several methods of image processing can be used to achieve different objectives concerning the image. This is an essentially important proviso since if there is no image at all, then processing cannot start at all; and it is for this precise reason that the acquisition of the image is invariably the first step in the processing sequence. Cameras and scanners are some of the instruments that can be used in the process of collecting visual information among several other devices. The acquired picture must retain every detail of its composition needed to associate the injury with the baldness.

I. Base Dataset

To obtain the images of the pepper crops with six different diseases and also the control, the dataset from Plant Village was employed. All the said photographs are presented as jpegs with a displayed resolution of 256 × 256 pixels. The sample of the Standard Dataset (Plant Village Database) is shown in the following Figure No.(4).

Figure 4. The sample of the Plant Village dataset

B. Enrolment Phase

In this step, the final recipient of the entire enrollment features is the system's training. Additional sub-steps make up the enrolling phase:Additional sub-steps make up the enrolling phase:

I. Preprocessing Image

The procedure starts with the application of picture pre-processing to improve the quality of pictures of plant disease affected leaves. This method is used because photographs do not always taken in ideal conditions (for instance too much light, noise, or big file size and the like), and will make the efficiency of the image enhanced in such a way that it will display the image detail.

A. Resize Image for Plant Leaf Diseases

It will do the proper image size since the system desires a superior turn and boost the plant disease figure. This is because, artificial neural network inputs have fixed size, hence image dimensions are resized to the required size of the structure of the network. These dimensions are may be obtained by applying the approach on the image and when we resize the image, no portion of the image's information is lost.

II. Feature Extraction

When identifying the diseases in a particular plant, the most important of the two procedures involves feature extraction from samples of the diseases, such as the plant leaf diseases. In the main proposed system, the CNN is used, and the convolutional layer plays its role at the level of the extraction of features. The CNN architecture is illustrated in Figure 5, which provides a detailed explanation of each layer:The CNN architecture is illustrated in Figure 5, which provides a detailed explanation of each layer:

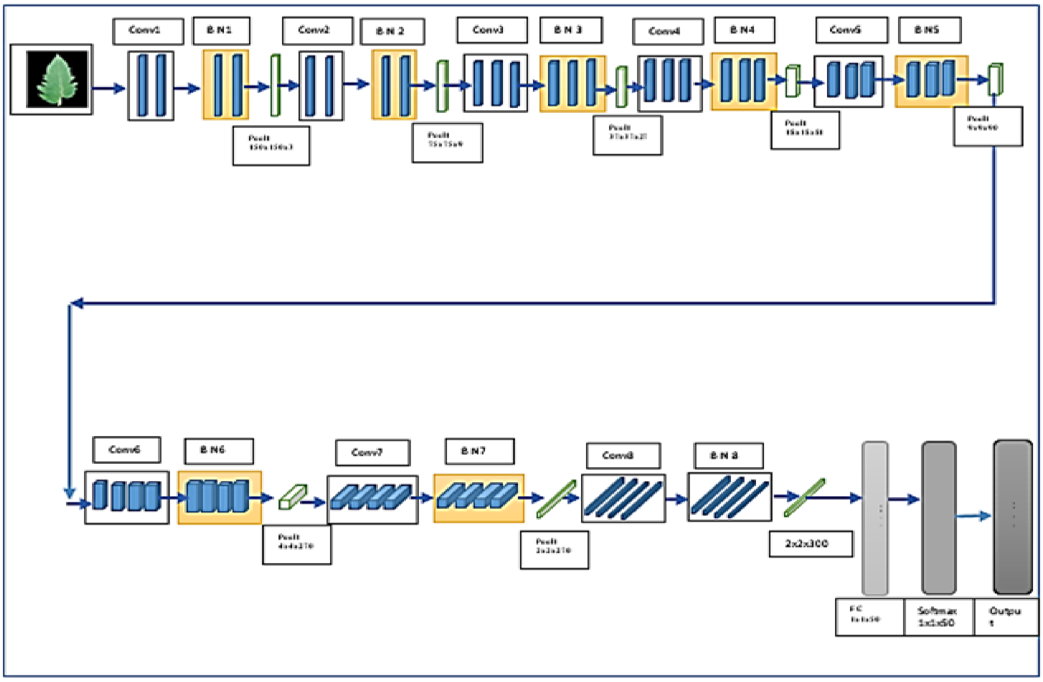


Figure 5. Architecture of Convolutional neural network.

1. Convolutional Layer

The feature extraction layer weights take an image, perform dot product multiplication and then shifts a weighted mask over it in order to come up with a feature map . For getting the appropriate weight in this image which is substitute of the feature, weight is randomly generated and then it is consecutively fed through BN, Pooling and RleU layers. 2. Batch Normalization Layer (BN)

This layer reduces the number of the channels used in order to make the training process faster and less dependent from the networks initials. To do this, it does the following: First, it scales the activation of each channel in the cabinet where they use equation 2 to standardize the mini batch where the mean is subtracted from the activation and then divided by the standard deviation of the same mini batch. After, it displaces it to the location H and scales the input by the factor of γ. Located between the RleU and the convolutional layer.

3. Max Pooling Layer

Using a max pooling layer to drop unessential features, this layer gathers data that is useful by dragging a mask of identifiable dimensions over a feature map resultant from the previous convolutional layer; however, there is no max, and hence, the highest value at every step remains unknown, hidden beneath the mask.

4. RleU Layer

The rectifier function is used to increase non-linearity of the image as it is required because images intrinsically contain non-linear elements such as colour and borders. The RleU layer, on the other hand, is used to ensure that only strong features are available and that all the negative ones are not considered by making all the numbers negative and taking only the positive ones.

5. Fully Connected Layer

Therefore, the most important information of the input data is encoded in a feature vector, which is used in various problems. Throughout training, it extracts features from loads of the convolutional layers so that it will be useful for classification at a later time. that is, teach the hidden layer to output the probability of each class.

6. Softmax Layer

Every class has a probability value like (0. 011, 0. 005) and the resulting value of Soft-max layer is a number between zero and one (0 and 1). Hire many candidates for the candidate class and shrink the number of the remaining classes.

7. Loss Function Layer

The loss function not only represents the difference between the expected output and the opted output but also used in the weight update process in backpropagation; It is used in order to calculate the loss (error) at each epoch in the trading environment.

C. Matching and Decision Stage

The geometric distance is a measure of the separation between two points on a coordinate system. as a result, settle on the chosen method of identification Matching process that uses distance in the standard geometrical sense. Every class has its own set of upper and lower limits; if the inspected sample's distance value falls somewhere in the middle of those limits, it is considered to be a member of that class.

4. Experimental Results

- ***a.*** Objects having unique, non-repeated texture patterns yield the best results when using this object detection approach. This strategy probably won't work with things that have a consistent colour scheme or patterns.
- ***b.*** ***Pre-processing stage:*** At this crucial stage, as illustrated in Figures (6), the original image is grayscaled and the ROI is extracted.

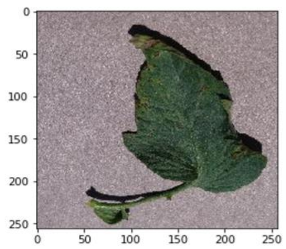
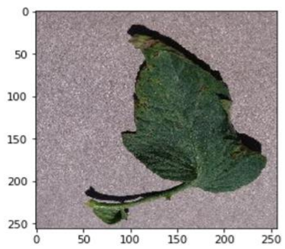
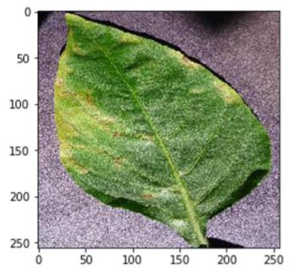
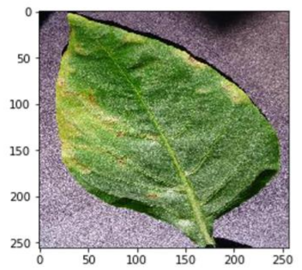
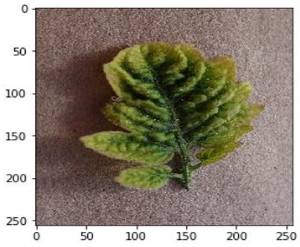
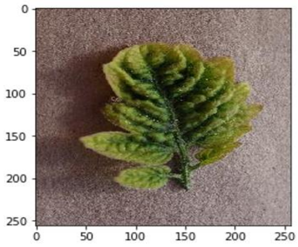
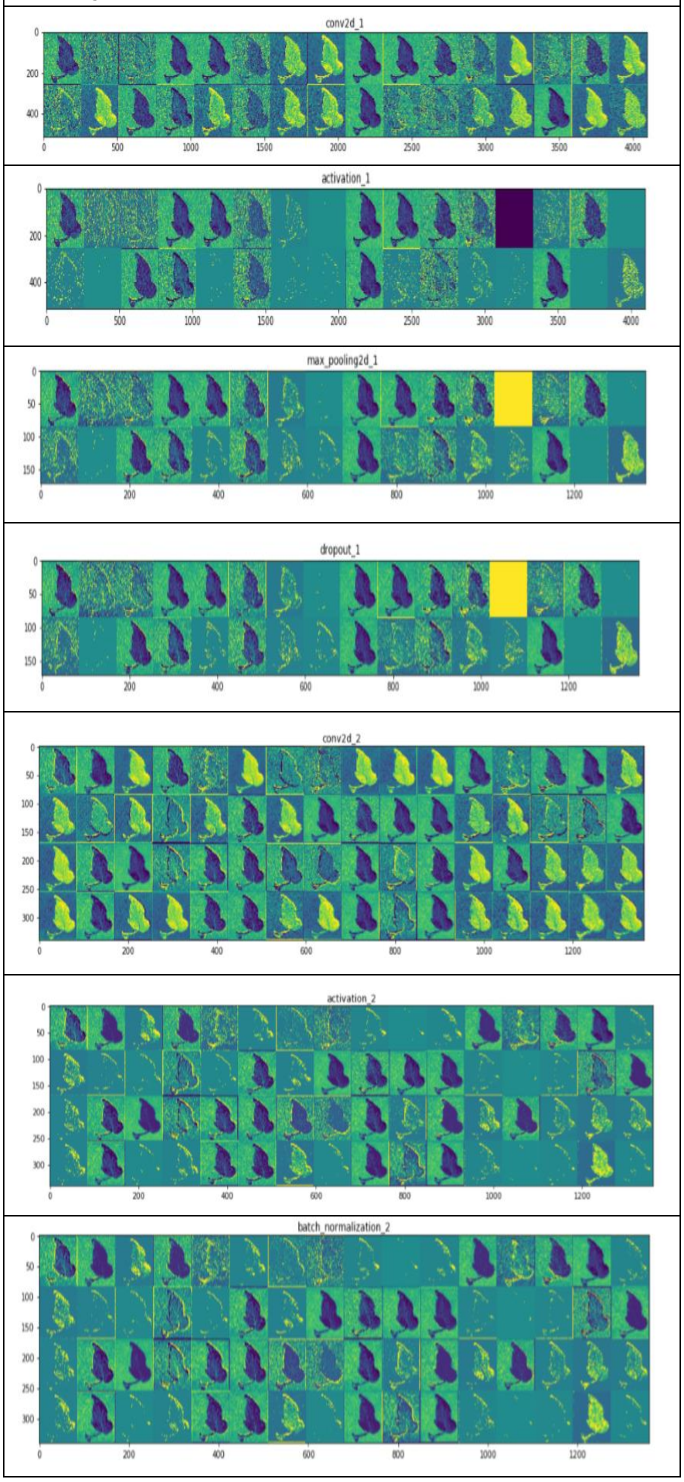
Resize Image	
 **dimension=1600x1200**	 **dimension=25x1200**
 dimension=1600x1200	 dimension=1600x1200
 dimension=1600x1200	 dimension=1600x1200

Figure 6. Resize Image

b. Convolutional neural network (CNN is the type of neural network primarily used in image processing.

Feature extraction is always the central part of any plant disease detection system. In a CNN, the convolutional layer, such as conv_, is the Feature map or Feature extraction layer. It performs a dot product multiplication by sliding a 'weight mask' over the input image; the product is a feature map. conv_1 feature map is passed to Batch Normalisation Layer (batchnorm_1) where number of feature map is reduced to facilitate training faster. It then passes through the first of the max-pooling layers in which it only transmits the high values of an important aspect and discards the others, thereby enhancing the disparity between the features. The output of each layer in CNN is illustrated in the following figure. In this case, the following layer, RleU, reduces the size of the feature map by removing negative values in order to ensure that specific features are retained only.

All layer of CNN



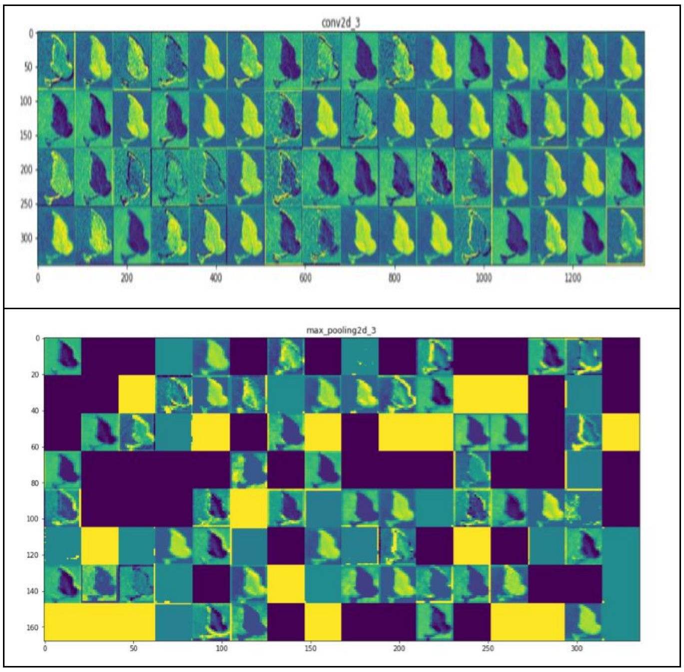


Figure 7. The output of each convolutional layer on CNN

Conclusion:

The purpose of this research is to present a novel method for deep learning-based automatic identification and detection of herbal illnesses from leaf photos. The purpose of developing the model was to find out which leaves were involved and to distinguish between healthy leaves and thirteen visually discernible illnesses. The complete procedure was specified by first defining the image sets utilised for testing and evaluation, then by pre-processing and extending the images, and lastly by testing and fine-tuning the deep convolutional neural network (CNN). To ensure the newly constructed model is effective, a large number of experiments have been conducted. The new plant disease picture repository started with more than 3,000 images sourced from the internet and was later enhanced with over 30,000 images thanks to accurate transformations. For individual class inspections, the results of the experiments showed an accuracy of 91% to 98%. The trainer qualified with an average finish rate of 96.3%. While the cycle of improvement had a bigger impact on performance, fine-tuning did not show any significant gains in average precision.

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