

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 7, Special Issue 3, March 2018

Plant Disease Detection Using IOT

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ABSTRACT: Diseases in plants cause major production and economic losses as well as reduction in both quality and quantity of agricultural products. Now a days plant diseases detection has received increasing attention in monitoring large field of crops. Farmers experience great difficulties in switching from one disease control policy to another. The naked eye observation of experts is the traditional approach adopted in practice for detection and identification of plant diseases. On the other hand, mobile phone usage has increased exponentially among the population of India. People from all walks of life are using mobile phones and different associated applications for gaining economic and social benefits. However, very few mobile phone applications benefit agricultural production and specifically aim farmers. In the proposed paper we review the need of simple plant leaves disease detection system through an android application that would facilitate advancements in agriculture. The project is aimed at developing an android application to generate an automated mobile-based system to detect diseases of tomato through image processing of leaves. The purpose of such development is to assemble an application with a user friendly interface and implement some effective algorithms considering the problems. This will improve productivity of crops.

KEYWORDS: Image processing, eclipse, android.

I. INTRODUCTION

An India is basically an agricultural country, and the near about 65% of the income is based on the agricultural production, and all its resources depend on the agricultural output. In Agricultural Department technology are rapidly changing, many automatic technology are came in the market, ex. Automatic cutter machine, etc. which is helpful to farmer to produce maximum product. The total rainfall in a particular area may be either insufficient, or ill-timed. In order to get the maximum production yield, it is essential to supply the accurate quantity and quantity of water as well as medicine, and maintain correct timing of water and medicine. This is possible only through a systematic irrigation system-by controlling and secluding the motors. The different methods of supplying water to the farm are Surface irrigation; Sub-surface irrigation and Sprinkler irrigation, also some method for supplying the medicine to the plant is spray-by handle pump, automatic pump and sub-surface irrigation. In irrigation the water plays main role if we gives the more than sufficient water there may be chance to effect on the plant, then if plant get disease then how the farmer knows the which type of disease are effected to the plant and in what percent the plant is effected by the disease.

II. BACKGROUND

Since the beginning of agriculture, farmers have developed methods for managing weeds, insect pests and diseases. Due to the significant impact from pests and diseases, on both human and animal health, it is important for those interested in plants to develop a firm understanding of weed science, entomology (study of insects) and plant pathology (study of plant disease), and how to minimize losses caused by these important plant pests.

All plants, native and cultivated, are prone to diseases and injuries. There are many definitions of plant disease. One definition is that disease is suboptimal plant growth brought about by a continuous irritant, such as a pathogen (an organism capable of causing disease) or by chronic exposure to less than ideal growing conditions. In contrast, injury is loss of plant vigour resulting from an instantaneous event, such as a lightning strike, hail damage, chemical burn or mechanical damage. Because of the instantaneous and "cause-and-effect" nature of injuries, they are often easy to

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diagnose. In the case of diseases, the effects are caused by a continuing process or irritation. The source of continuous irritation may be abiotic (non-living) or biotic (caused by a pathogen). Abiotic diseases are also referred to as non-infectious diseases as they do not spread from plant to plant. Examples can include nutrient deficiencies growing under too much or too little light, and air pollutants such as automobile exhaust. Biotic diseases are caused by pathogens and are often referred to as infectious diseases, because they can move within and spread between plants. Plant pathogens are very similar to those that cause disease in humans and animals and include viruses, bacteria, fungi, and nematodes. Pathogens may infect any part of the plant including leaves, shoots, stems, roots, fruit, and seeds. For an infectious disease to develop, a susceptible host, a pathogen capable of causing disease and a favourable environment for the pathogen to grow is required. If any one of these factors is absent, disease will fail to develop. In the case of infectious plant diseases, practices that favour plant growth over pathogen activity tend to decrease the amount of disease observed. For example, plants that are fertilized and watered correctly will be less likely to develop disease. Regardless of which pathogen, disease development on a plant requires that the pathogen must: (a) come into contact with a susceptible host (referred to as inoculation); (b) gain entrance or penetrate the host through either a wound, a natural opening on plant surface (stomata, lenticels, etc.) or by direct penetration of the host; (c) establish itself within the host; (d) grow and multiply within or on the host; and (e) be able to spread to other susceptible plants. Successful pathogens must also be able to survive long periods of unfavorable environmental conditions in the absence of a susceptible plant host. Together, these steps are referred to as the disease cycle. If this cycle is broken, the disease will be less severe or fail to develop. Two terms that are often used when discussing plant disease and injury are sign and symptom. In the medical field, the two words are used differently than in the plant world. In dealing with plants, the word sign is used when the pathogen or part of the pathogen is observed in or on an infected plant. Examples include: fungal hyphae or mycelium, spores, fruiting bodies, bacterial cells, or virus particles. Symptoms are visual or noticeable changes of a plant which result from disease or injury. Early after infection, disease symptoms are often invisible since they take time to develop. Examples of common symptoms are: yellowing of leaves; wilting of leaves; drooping of leaves or fruit; and stunting of plant parts or the whole plant.

III. METHODS

1. Dataset Description

We analyse 54,306 images of plant leaves, which have a spread of 38 class labels assigned to them. Each class label is a crop-disease pair, and we make an attempt to predict the crop-disease pair given just the image of the plant leaf. **Figure 1** shows one example each from every crop-disease pair from the Plant Village dataset. In all the approaches described in this paper, we resize the images to 256×256 pixels, and we perform both the model optimization and predictions on these down scaled images. Across all our experiments, we use three different versions of the whole Plant Village dataset. We start with the Plant Village data set as it is, in colour; then we experiment with a grey-scaled version of the Plant Village dataset, and finally we run all the experiments on a version of the Plant Village data set where the leaves were segmented, hence removing all the extra background information which might have the potential to introduce some inherent bias in the data set due to the regularized process of data collection in case of Plant Village dataset. Segmentation was automated by the means of a script tuned to perform well on our particular dataset. We chose a technique based on a set of masks generated by analysis of the colour, lightness and saturation components of different parts of the images in several colour spaces (Lab and HSB). One of the steps of that processing also allowed us to easily fix colour casts, which happened to be very strong in some of the subsets of the dataset, thus removing another potential bias. This set of experiments was designed to understand if the neural network actually learns the "notion" of plant diseases, or if it is just learning the inherent biases in the dataset.

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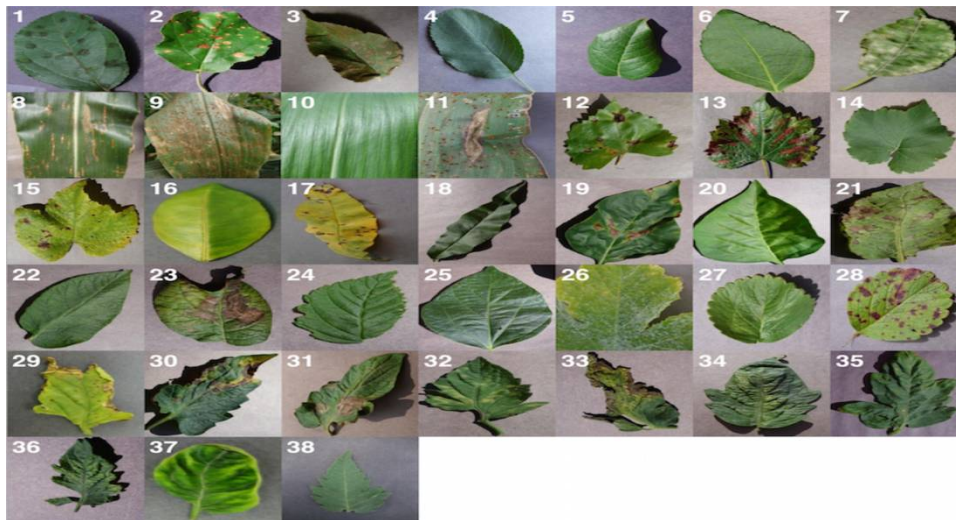


FIGURE 1|Example of leaf images from the Plant Village dataset, represent in every crop disease pair used.

(1) Apple Scab, *Venturiainaequalis* (2) Apple Black Rot, *Botryosphaeriaobtusa* (3) Apple Cedar Rust, *Gymnosporangiumjuniperi-virginianae* (4) Apple healthy (5) Blueberry healthy (6) Cherry healthy (7) Cherry Powdery Mildew, *Podoshaeraclandestine* (8) Corn Gray Leaf Spot, *Cercosporazeae-maydis* (9) Corn Common Rust, *Pucciniasorghii* (10) Corn healthy (11) Corn Northern Leaf Blight, *Exserohilumturcicum* (12) Grape Black Rot, *Guignardiabidwellii*, (13) Grape Black Measles (Esca), *Phaeomoniellaaleophilum*, *Phaeomoniellachlamydospora* (14) Grape Healthy (15) Grape Leaf Blight, *Pseudocercosporavitis* (16) Orange Huanglongbing (Citrus Greening), *CandidatusLiberibacterspp.* (17) Peach Bacterial Spot, *Xanthomonascampestris* (18) Peach healthy (19) Bell Pepper Bacterial Spot, *Xanthomonascampestris* (20) Bell Pepper healthy (21) Potato Early Blight, *Alternariasolani* (22) Potato healthy (23) Potato Late Blight, *Phytophthorainfestans* (24) Raspberry healthy (25) Soybean healthy (26) Squash Powdery Mildew, *Erysiphecichoracearum* (27) Strawberry Healthy (28) Strawberry Leaf Scorch, *Diplocarponearlianum* (29) Tomato Bacterial Spot, *Xanthomonascampestris* sp. *vesicatoria* (30) Tomato Early Blight, *Alternariasolani* (31) Tomato Late Blight, *Phytophthorainfestans* (32) Tomato Leaf Mold, *Passalorafulva* (33) Tomato Septoria Leaf Spot, *Septorialycopersici* (34) Tomato Two Spotted Spider Mite, *Tetranychusurticae* (35) Tomato Target Spot, *Corynesporacassiicola* (36) Tomato Mosaic Virus (37) Tomato Yellow Leaf Curl Virus (38) Tomato healthy.

Appropriate datasets are required at all stages of 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. Next step was to enrich the dataset with augmented images. The main goal of the presented study is to train the network to learn the features that distinguish one class from the others. Therefore, when using more augmented images, the chance for the network to

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learn the appropriate features images for training and 2589 images for validation has been created. The augmentation process is described in Section 3.

2. Image Pre-processing and Labelling.

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 was pre-processed in order to gain consistency. Furthermore, procedure of image pre-processing 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 [33]. Many resources can be found by searching across the Internet, but their relevance is often unreliable. In the interest of confirming the accuracy of classes in the dataset, initially grouped by a keywords search, agricultural experts examined leaf images and labelled all the images with appropriate disease acronym. As it is known, it is important to use accurately classified images for the training and validation dataset. Only in that way may an appropriate and reliable detecting model be developed. In this stage, duplicated images that were left after the initial iteration of gathering and grouping images into classes described in Section 1 were removed from the dataset.

3. Augmentation Process.

The main purpose of applying augmentation is to increase the dataset and introduce slight distortion to the images which helps in reducing overfitting during the training stage. In machine learning, as well as in statistics, overfitting 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. Transformations applied in augmentation process are illustrated in Figure 2, where the first row represents resulting images obtained by applying affine transformation on the single image; the second row represents images obtained from perspective transformation against the input image and the last row visualizes the simple rotation of the input image. The process of augmentation was chosen to fit the needs; the leaves in a natural environment could vary in visual perspective.

For this stage, in order to automate the augmentation process for numerous images from the dataset, particular application was developed in C++ using the OpenCV library, with possibility of changing the parameters of transformation during the run-time, which improves flexibility.

4. Neural Network Training.

Training the deep convolutional neural network for making an image classification model from a dataset described in Section 1 was proposed.

There are several well-known state-of-the-art deep learning frameworks, such as Python library Theano and machine learning library that extends Lua, Torch7. In addition, there is Caffe, an open source deep learning framework developed by the BVLG containing reference pretrained CaffeNet model. For the purpose of this research, this framework was used, along with the set of weights learned on a very large dataset, ImageNet [40]. Caffe framework is suitable for both research experiments and industry deployment. The core of framework is developed in C++ and provides command line, Python, and MATLAB interfaces. Caffe's integration with cuDNN library accelerates Caffe models. CaffeNet is a deep CNN which has multiple layers that progressively compute features from input images

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. Specifically, the network contains eight learning layers and five convolutional and three fully connected layers. CaffeNet architecture is considered a starting point, but modified and adjusted to support our 15 categories (classes). Last layer was altered and the output of the softmax layer was parameterized to the requirements of presented study. The convolutional layer is the essential building block of the convolutional neural network. The layer's parameters are comprised of a set of learnable kernels the layer's parameters are comprised of a set of learnable kernels which possess a small receptive field but extend through the full depth of the input volume.

IV. CONCLUSIONS

There are many methods in automated or computer vision plant disease detection and classification process, but still, this research field is lacking. In addition, there are still no commercial solutions on the market, except those dealing with plant species recognition based on the leaves images. 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 diagnosed. The complete procedure was described, respectively, from collecting the images used for training and validation to image pre-processing 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. New plant disease image database was created, containing more than 3,000 original images taken from the available Internet sources and extended to more than 30,000 using appropriate transformations. The experimental results achieved precision between 91% and 98%, for separate class tests. The final overall accuracy of the trained model was 96.3%. Fine-tuning has not shown significant changes in the overall accuracy, but augmentation process had greater influence to achieve respectable results. As the presented method has not been exploited, as far as we know, in the field of plant disease recognition, there was no comparison with related results, using the exact technique. In comparison with other techniques used and presented in Section 2, comparable or even better results were achieved, especially when taking into account the wider number of classes in the presented study. An extension of this study will be on gathering images for enriching the database and improving accuracy of the model using different techniques of fine-tuning and augmentation. The main goal for the future work will be developing a complete system consisting of server side components containing a trained model and an application for smart mobile devices with features such as displaying recognized diseases in fruits, vegetables, and other plants, based on leaf images captured by the mobile phone camera. This application will serve as an aid to farmers (regardless of the level of experience), enabling fast and efficient recognition of plant diseases and facilitating the decision-making process when it comes to the use of chemical pesticides. Furthermore, future work will involve spreading the usage of the model by training it for plant disease recognition on wider land areas, combining aerial photos of orchards and vineyards captured by drones and convolution neural networks for object detection. By extending this research, the authors hope to achieve a valuable impact on sustainable development, affecting crop quality for future generations.

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