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PLANT DISEASE DETECTION USING DEEP LEARNING: A SURVEY

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Abstract: Rapid and accurate identification of plant diseases is essential for sustainable increases in agricultural productivity. Human experts have traditionally been relied upon to diagnose diseases, pests, nutritional shortages, and severe weather abnormalities in plants. This however is costly, time-consuming, and not practicable in some situations. The study of the use of pictorial methods for plant recognition has become a hot topic to address these challenges. We review the recent studies in the field of identifying pesticides and diseases utilizing imaging and machine learning in this paper. We expect this work to serve as a valuable resource for researchers who use image processing techniques to recognize crop pests and disease. In particular, we concentrate on the use of RGB images due to the low cost and high accessibility of RGB cameras. Deep learning instead of superficial classifications using manufactured characteristics has been at the forefront of recent efforts. The accuracy of the recognition on a specific dataset has been recorded by researchers; in some cases, the performance of these systems has deteriorated significantly when assessed on different datasets or under field conditions. However, it was promising to make progress to date. The experimental findings are present in ten CNN leaf disease recognition architectures, showing the accuracy, memory, precisely, specification, F1 score, training duration, and storage specifications. Recommendations are subsequently provided on the most appropriate architectures to be used in both traditional and mobile computing environments. We also explore some outstanding issues to be tackled to establish realistic systems for recognizing automatic plant diseases in field conditions.

Keywords**: Plant disease detection; Classification; Machine Learning, Convolutional Neural Network.**

I. INTRODUCTION

On the planet, there are several types of plant illnesses. These diseases may result in a decline in the quality of agricultural products and significant loss of returns and even threaten food safety. Prompt detection and diagnosis of herbal diseases is the foundation for disease control steps. Plant diseases are normally recognized and diagnosed by agricultural technicians based on visual recognition in-field. This method requires a high level of professional competence and extensive expertise and requires numerous staff. Pathogens diagnosis by disease detection requires more technical expertise and satisfactory laboratory conditions.Pathogens were quickly developed based on molecular biological techniques and the diagnostic results of these approaches could be obtained. These methods should, however, be carried out by technical and professional staff and cannot be carried out in the field. In addition, these approaches are temporary and costly. An easy and fast method of identification of plants with high identifying accuracy is therefore very important. The acquisition, processing, and transmission of information on plants have been significantly influenced by data technology with the rapid development of IT and agribusiness[1]. The broad concern arising from the progress of visual technology and the popularity of digital goods is now a recognition of plant diseases. Studies have been published on the identification and automatic evaluation of image-built plant conditions [2], [3], [4], [5], [6], [7], [8], [9] and [10].

Figure 1: All the classes of plant disease present in the dataset

Automated computer-based identification and diagnosis based on plant disease symptoms may provide agricultural technicians and farmers with rapid and accurate disease information, thereby reducing dependency on farm technicians.

Agricultural land in Bangladesh. Roughly 80% of people are directly or indirectly linked to agronomy. The economy of Bangladesh is heavily dependent on the agricultural sector and most of Bangladesh's economy is in this sector. The cultivation of crops and fruits for many years is changing our financial status.Many plants are planted across the country in Bangladesh and rice, wheat, and potato have affected the high level of popularity amongst all crops and fruits. Maize, peach, grape, and strawberry plantation is showing a growing trend, which is quickly strengthened by the invitation of this crop. Thus, farmers' interest in growing such crops and fruits is higher than the previous decline.
The fish is very common and highly tested for vitamin A products. In the hemisphere of the northern and southern regions, fish grows at colder temperatures.Peach has been invented in China for the first time, since spreading Asia, Europe, Spain, Mexico, and the US. The fruit tree size is very short of peach (Prunus persica).The peach farmer has suffered various diseases that have decreased the production rate of the peach and caused enormous losses. Several diseases are present, such as Pseudomonas syringae, Crown gall (Agrobacteiumspp), Scab (Cladosporium carpophlum), Bacterial spot (Xanthomonas campestris), Brown Red (MoniLinefructicola) Rust (Tranzscheliadiscolour), and short hole illness. Are they present? (Wilsonomycescarpophilus). The blades on the bottom of the tree turn violet in the center during the bacterial spot. The surface of the fruits introduces tiny, circular spots with green color when faced with Scab disease and its size gradually increases to the dark yellow halo. The skin and tissue of fruit lose color during Brown red disease. The top and bottom of the peach are yellow-green in angular form. The new leaf is red and the leaf is unregulated raised as leaf curl disease. It becomes red with a yellow hue.

1.1 Plant Disease Detection

Plant disease identification plays a significant role in agriculture because farmers often have to determine if the crop is healthy enough to harvest. Taking this very seriously is essential because it can cause severe problems on plants. After all, the consistency, quantity, or efficiency of the respective products are affected. Plant diseases trigger a frequent epidemic of large-scale deaths that have a serious effect on the economy. To save people's lives and resources, these issues have to be fixed at first.A significant research subject is the automatic classification of plant disease as it is important for monitoring large crop fields and at a very early stage if we can identify disease symptoms as they occur on the leaves of plants. This allows image-based automated inspection of computer vision algorithms. In comparison, labor-intensive manual recognition is less reliable and can only be performed in small areas at once.This approach allows for the initial detection of plant diseases and for the resolution of pest problems with reducing risks to people and the environment, it also allows us to use pest control methods.

I. II. REVIEW OF TECHNIQUES USED

In plants that have diseases, the leaves, roots, flowers, and/or fruits are normally affected with noticeable marks or lesions. Generally, a single recognizable pattern may be used for the diagnosis of the abnormality of each disease or insect. Extension officers are qualified by visual examination or laboratory testing on plant samples for diagnosing pesticides and diseases. But there are some drawbacks to these approaches: To cover all farms, extension officials are always too few.
In crucial times, many farmers can be without extension services[13]. Enlargement officer training is expensive and time-consuming.It might not be possible for farmers or extension officers to properly identify native diseases and pests[7]. To differentiate between anomalies with visually similar properties, a high degree of expertise is needed [13]. In such circumstances, exhaustion, inadequate lighting, or bad vision can still lead to misdiagnoses by even a highly qualified specialist. In addition, specialists in a limited number of disorders sometimes specialize[15].

- Early disease identification and the prevention of disease transmission must be monitored continuously. This is boring, time-consuming, and ongoingly expensive, and ineffective [13].
- Laboratory tests are often destructive in addition to high laboratory equipment, as they also collect samples from the field and take them to a laboratory for testing.

In addition, the transfer of samples to the laboratory may be limited by quarantine.

2.1 Leaf disease recognition based on hand-crafted feature extraction

The general workflow is shown in Fig. 1 after earlier work on the automatic identification of leaf diseases. The image capture includes photographic details collected using an appropriate camera. Pre-processing of images is performed on the recorded images to improve the image quality. E.g., redimensioning, filtering, color conversion, and histogram equalization are examples of processes at that point. Segmentation is double in plant disease identification applications. The division shall first be carried out to separate from the background the leaf, fruit, or flower.A second segmentation is then rendered so that healthy tissue is separated. Extracting information from the segmented picture requires mining information that could enable an accurate anomaly classification. A texture (energy, contrast, homogeneity, and correlation), form, dimensions, and color could be characteristics that could be extracted. Statistical measures such as Local Binary Pattern (LBP), Gray Level Matrix, Co-Occurrence Color Matrix (CCM), and Gray Spatial Dependency Matrix Matrix can derive textual features (SGLDM). Modeling methodologies including Autoregressive (AR) and Random Field (MRF) models from Markov can also be used to extract textural characteristics.

2.2 Leaf disease recognition using deep learning Techniques

In recent years, CNN's in image recognition tasks such as ImageNet have shown excellent performance. Classifying and Function Extractors. The concept was applied to agricultural applications with a view, for example, to identify diseases, recognize the plague, detect weeds, count fruit and flora, and sort and grade fruit. Most study in the identification of leaf diseases via IPTs has taken advantage of profound learning since 2015[15].LeCun et al.defined deep learning as a way to represent information by using a range of optimisms instead of semantic features. the algorithm finds the best way of representing data. There is no need for functional engineering with this learning technique as features are extracted automatically.

In the fields of malaria diagnostics, pest identification, quality control, marketing, automation, robotics, and big data, deep learning can help advance the agricultural industry. For training CNNs, large data sets of dozens of images are required.Unfortunately, such large and complex datasets have not yet been compiled and used by researchers in the field of plant disease identification. Transfer learning is currently the best method of training robust CNN classifiers for the identification of plant diseases. Transfer education makes it possible to adapt retrained CNNs by retraining them using smaller datasets that vary from larger data systems traditionally used to train the network from scratch. The study shows that the ImageNet dataset uses pre-trained CNN models and then recycles them to detect conditions in the leaf.

A dataset of 4483 photos from the internet was collected by the authors [9]. They chose Caffe's profound method and demonstrated that CaffeNetCNN's pre-trained architecture can be adapted for bladder disease detection through transfer learning.The authors recorded 95.8% of high accuracy before finishing the model and 96.3% after finely tuning. In Mohanty and others, 60 blue disease identifying experiments are performed on the AlexNet and Google-Net CNN architecture with the PlantVillage dataset. As shown in Table 2 below, the authors used different trainingtests, different mechanism choices, and different types of data sets. For each setup, the Caffe deep learning system has conducted training with 30 structured epochsus hyperparameters. The authors recorded excellent accuracy in all experimental configurations with a mean F1 scorer of over 85 percent.F1 scores of over 99 percent were the best results. GoogLeNet has consistently exceeded other configurations using transfer learning.

Best results were also obtained with the use of initial RGBimages in comparison with grayscale or RGBimages.

The performance also improved as images used for training were increased to those used for research.

However, accuracy dropped to 31% when the most effective model was tested with field conditions. With a particular dataset, the ability of the system to generalize well-defined field conditions remains unresolved.

Table 2.1 – Experimental parameter configuration options

Training parameter	Options
Choice of deep learning architecture	AlexNet or GoogLeNet
Choice of training mechanism	Transfer Learning or Training from Scratch
Choice of dataset type	Colour or Grayscale or Leaf Segmented
Train:80%, Test:20% or Train:60%, Test:40% or Train:50%, Test:50% or Train:40%, Test:60% or Train:20%, Test:80%	

III. METHODS

The steps to create and deploy the classification are described in this section. Classification by CNN is divided into three phases dealing with individual activities.

A. Data Acquisition

'The PlanVilllage Dataset,' an open-access repository with a total of 54,323 images is the product of all Potato and Tomato images. All Rice imagery originates from the "Rice Diseases Image Dataset" Kaggle dataset.

In a controlled environment, all pictures are collected. This is supposed to lead to model bias. A test dataset of 50 images originating from Google will also be created to access this. These photos contain more plant anatomy, background data on the field, and different disease stage.

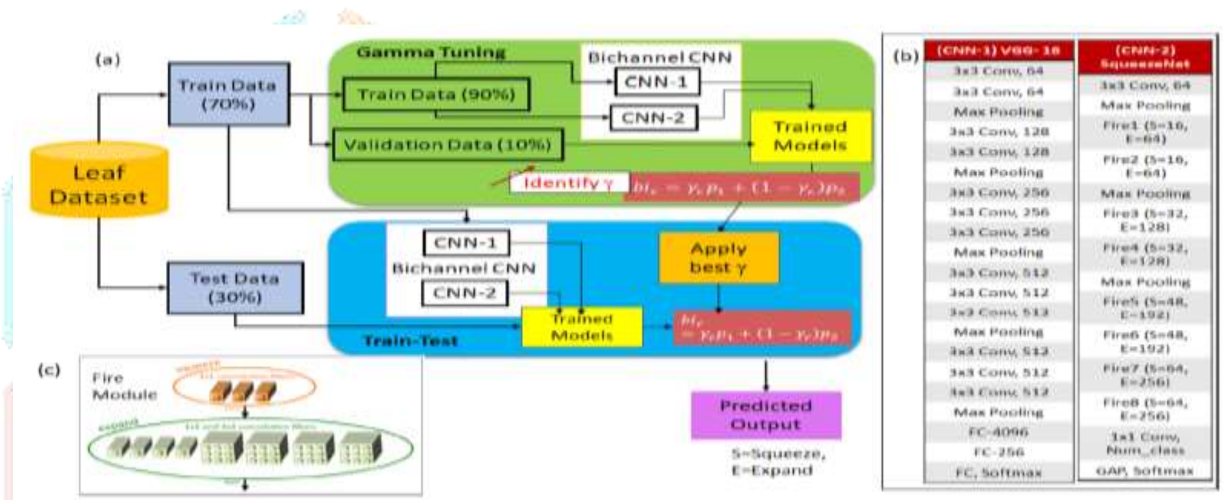

Figure 2 Workflow for Bi-channel Convolution Neural Network. (a) Workflow (b) CNN-1 and CNN-2 (c) SqueezeNet's Fire Module

B. Data Pre-Processing

For training and validation, the dataset is divided into 80% and 20%. First, increase settings for the training data are applied. These are generated on the fly, with a weighted probability of appearance in each operation at any time.
Flipping (random), padding (reflecting) and zoom with crop (scale = (1.0,1.5)) are the setting used. 'Crop zoom' later was removed following its discovery that areas of the contaminated leaf had been improperly clipped.All pictures are finally re-sized and normalized. Redimensioning to 150 x 150 is done with a compressing tool. The RBG ImageNet statistics are used for standardization as a pre-trained model.

C. Classification by CNN

1) Phase One – Trialing of Image size

Phase I is designed to study the impact on model efficiency that the image size has. Five photos of 150 x 150 to 255 x 255 are tested in total. Initially, weight training is downloaded from Resnet34. Both layers, except the last two layers, are frozen as a default of transfer learning. These include new weights and are unique to the classification of plant diseases. Freezing allows for the independent training of these layers without reproducing the pitches. This is the precise way to train the final layer in the 1 cycle policy.

2) Phase Two – Model Optimization

The ResNet34 model is configured by the most appropriate image scale. Additional increase settings are applied to further boost the model's performance.
The final two layers will then be separated and trained at the standard learning pace. With this finished tuning, several studies are carried out to measure a range of rates and epochs of education.

3) Phase Three – Visualizations

A series of visualizations based on the validation and test datasets are created for interpretation purposes. Furthermore, the model is used to build a web app. The completed critical files are stored in a GitHub repository and exported as a pickle file for this purpose. The repository is related to the unified framework for the implementation of the model; Render. The GitHub 'Render Examples' repository was used as a reference when performing this task.

CONCLUSION

In this analysis, it is observed that PCA and Convolutional neural networks were used for the identification of images of plant diseases based on the colors, form, and texture characteristics derived from and combined with images from disease. As the results showed, the reduction of feature data derived from plant disease pictures could reduce neural network operational time and provide satisfactory reconnaissance results. The process employed in this study may also be used to detect images of other plant diseases.PCA could be applied in practical applications to reduce the dimensions and to create optimal neural networks for the identification of plant disease data derived from the plant disease images. When images of plant diseases are detected on personal computers, the operation to reduce the size of data obtained is not necessary and the speed of recognition cannot be substantially impacted by the increased computer performance and the strong neural network's ability to resolve problems.When plant diseases are recognized based on several extracted features on the Internet, the size of the data acquired should be reduced first, and then the picture recognition can be carried out using neural networks.

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