Image-Based Plant Disease Detection by Comparing Deep Learning and Machine Learning Algorithms

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Abstract
Plant diseases are one of the most serious issues in agriculture. As population increases, the number of plants in addition can increase and due to plant diseases it's going to have a control on the assembly of food. The traditional methodology used for illness detection is knowledgeable visual observation. It's very sophisticated to go look out the illness manually as a result of the time interval and knowledge of the plant's diseases. So, it had been necessary to develop a system that detected the illness in less time and value effective manner. We discuss the employment of machine learning and deep learning to sight diseases in plants automatically. Using a public dataset of fifty four thousand, three hundred photos of pathological and healthy plant leaves collected below controlled conditions, we tend to train a deep convolutional neural network to identify fourteen crop species and twenty six diseases (or absence thereof). The trained model achieves academic degree accuracy of ninety nine point three five percent on a held-out test set, demonstrating the practicability of this approach. Overall, the approach of coaching job deep learning models on additional and additional large and publicly out there image datasets presents a clear path toward smartphone-assisted illness identification on a huge world scale.

Keywords — machine learning, plant diseases, deep learning

I. INTRODUCTION

Plants are necessary not only as a source of energy, but also as the primary contributor to global warming and other environmental problems. Plant diseases cause severe harm to plants, which has a big impact on a country's economic prosperity. We need to catch the sickness as soon as possible. Plant infections had previously been diagnosed by experienced professionals who examined plant tissue carefully. Given the limitations of human intelligence, this was a costly and unsuccessful paradigm. The simplest technique to deal with this is to employ machine learning, which involves putting a picture of an infected plant's leaf into a neural network for disease diagnosis.

Plant infections were previously discovered by experienced professionals visually inspecting plant tissue. Because human intellect isn't perfect, this was a costly and ineffective paradigm. The ideal way to tackle this is to use machine learning, in which the image of an infected plant's leaf is pre-processed and fitted into a neural network model for disease diagnosis.

The analysis of RGB images is currently the most popular approach, because of recent developments in computer vision and the availability of inexpensive. Another reason for analyzing RGB photographs is that, given the widespread availability of smartphones, these solutions have the potential to reach even the most remote regions. Traditional machine learning (ML) techniques or the deep learning (DL) approach can both be used to analyze RGB photos. To detect the disease with the highest accuracy, traditional machine learning methods and deep learning algorithms are applied. Support Vector Machine (SVM), K-Nearest Neighbours (k-NN), Fully Connected Neural Networks (FCNN), Decision Trees, and Random Forests are examples of machine learning techniques.
II. LITERATURE SURVEY

Instead of utilizing traditional handmade methodologies, deep learning models have allowed researchers to build, train, and test the system from beginning to end. Because of the convolution neural network’s outstanding effectiveness as a feature extractor in image processing challenges, it has been applied to other applications such as digit recognition, agriculture, and robotics.

1) The global burden of pathogens and pests on major food crops
Authors: Savary, Serge, et al.

Plant diseases and pests reduce the yield and quality of agricultural products. They cause huge economic losses and jeopardize food security at the household, national, and global levels. Compiling and analyzing quantifiable, standardized data on crop losses across crops, agricultural systems, and locales can be difficult. For five major crops farmed around the world and in food-security regions, we give an expert-based assessment of crop health, as well as numerical estimates of yield losses due to disease and pest. 137 viruses and pests associated to wheat, rice, maize, potato, and soybean have caused losses over the world, according to our research. Our research indicates differences in the impact of plant pathogens and pests, as well as food security issues. This study provides critical information for prioritizing crop health management in order to improve the long-term viability of agroforestry systems as a source of society benefits. Pathogens and pests in crops, as well as food security hotspots This research provides crucial information for prioritizing crop health management in order to increase the long-term viability of agroecosystems in providing services to society.

2) Using deep learning for image-based plant disease detection
Authors: Mohanty, Sharada P., David P. Hughes, and Marcel Salathé

Crop diseases are a huge danger to food security, but due to a lack of infrastructure in many parts of the world, detecting them quickly is challenging. Smartphone-assisted disease detection is now achievable thanks to a combination of rising global smartphone usage and recent advancements in computer vision made possible by deep learning. We trained a deep convolutional neural network to identify 14 crop species and 26 diseases using a public dataset of 54,306 photos of damaged and healthy plant leaves taken under controlled settings (or absence thereof). On a held-out test set, the trained model achieves an accuracy of 99.35 percent, demonstrating the practicality of this strategy. Overall, the method of training deep learning models on increasingly vast and publicly available image datasets points to a clear route toward widespread global smartphone-assisted crop disease detection.

3) A practical plant diagnosis system for field leaf images and feature visualization
Authors: Fujita, E., et al.

An automated plant diagnosis system that is accurate, quick, and low-cost has been requested. While various research has been undertaken using machine learning approaches, significant concerns remain in most cases where the dataset is not made up of field photos and typically contains a large number of incorrect labels. We offer a viable automated plant diagnosis system in this paper. We start by cultivating plants in a highly controlled environment to create a highly trustworthy dataset. Then we create a robust classifier that can analyze a wide range of field photos. We used 9,000 genuine cucumber field leaf pictures to identify seven common viral infections, Downy mildew, and healthy plants, as well as early symptoms. The important areas of diagnostic evidence are also displayed. We confirm that our method catches crucial elements for the diagnosis of Downy mildew, with an average accuracy of 93.6 percent.
4) Textural features for image classification  
Authors: Haralick, Robert M., Karthikeyan Shanmugam, and Its’ Hak Dinstein

Whether the image is a photomicrograph, an aerial snapshot, or a satellite image, texture is one of the most essential qualities employed in identifying items or regions of interest. This research explains some easily computed textural elements based on gray-tone spatial dependencies and shows them using multispeciality imagery from the Resources Technology Satellite (ERTS) that includes seven land-use categories.

We employ two types of decision rules: one with convex polyhedral as decision regions (a piecewise linear decision rule) and another with rectangular parallelepipeds as decision regions (a rectangular parallelepiped decision rule) (a min-max decision rule). The data set for each experiment was split into two parts: a training set and a test set. The aerial computable textural features have a universal applicability for a wide variety of image classification applications, with a test set identification accuracy of 89 percent for photomicrographs and 82 percent for aerial computable textural features.

5) Support-vector networks  
Authors: Cortes, Corinna, and Vladimir Vapnik

The support-vector network is a unique learning machine for two-group classification problems. The machine is built to accomplish the following concept: input vectors are non-linearly mapped to a feature space with a large dimension. In this feature space, a linear decision surface is constructed. The learning machine’s tremendous generalization ability is enabled by the decision surface’s unique properties. The support-vector network concept had previously been used in a limited situation where training data could be separated without errors. In this study, the technique is extended to non-separable training data. The ability of support-vector networks with polynomial input transformations to generalize is demonstrated. In an Optical Character Recognition benchmark study, we compare the performance of the support vector network to that of various conventional learning approaches.

III. EXISTING SYSTEM

The human population is continually increasing, and with it comes an increase in the demand for food production. According to UN forecasts [1,] the human population would reach 9.7 billion in 2050, an increase of 2 billion from present. Given that the majority of population growth is expected to occur in the least developed countries (an increase of roughly 80% in the next 30 years), where food shortage is a major issue, it is straightforward to assume that reducing food waste in those countries is a top priority. The global yield loss is predicted to be between 20 to 40% [2], with many farms experiencing a total loss. Diseases that are easily disseminated can have a significant negative influence on plant production, even destroying entire crops. As a result, early disease detection and prevention are extremely important.

DISADVANTAGES

- Data Collection Problem
- It searches from a large sampling of the cost surface.

IV. PROPOSED SYSTEM

Traditional disease detection methods necessitate specialized hand inspection of plants. This process must be ongoing, and it might be prohibitively expensive in large farms or even inaccessible to many small farmers in remote areas. Plant Village Dataset [3] is utilized. It’s made up of photos of plant leaves taken in a controlled setting. There are 54 306 photos of 14 different plant species in total, organized into 38 different classes as species/disease pairs. Traditional methods rely on image pre-processing and feature extraction, which are then put into one of the machine learning algorithms. Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Fully Connected Neural Networks (FCNN), Decision Trees, Random Forests, and other algorithms are popular alternatives.

Advantages

- Machine learning algorithm optimizes both variables efficiently, continuous or discrete
- It generates a multitude of optimal solutions rather than a single one. As a result, multiple image segmentation results can be acquired simultaneously.
- Large number of variables can be processed at the same time.
V. CLASSICAL ML APPROACH

A. Region segmentation
Scaling photos to the same size, removing the background, and removing artifacts are common pre-processing processes while working on image categorization. These procedures were not necessary in our situation because the Plant Village dataset already included segmented and scaled photos. We further segmented these pictures to isolate potentially diseased leaf patches, which was accomplished by deleting any pixels whose green channel value exceeded that of the red and blue channels.

B. Feature extraction
Feature selection is most likely the most difficult and critical aspect of developing an ML algorithm. In order to select appropriate characteristics, extensive research and knowledge of the target domain are required. The GLCM is used to characterize the spatial relationship between adjacent pixels, i.e. the likelihood of two pixel values, \( i \) and \( j \), being at a distance \( d \) and an angle from one another. It is represented as a NON-dimensional matrix (\( N \) is the number of distinct pixel values), where \( G(i,j) \) denotes the number of times a pixel of value \( j \) occurred at a distance \( d \) and an angle \( a \) from a pixel of value \( i \). The GLCM can be used to extract texture features such as correlation, contrast, energy, homogeneity, and dissimilarity.

Color characteristics are extracted from image histograms using statistical features. They’re used to give a general description of the image’s color statistics.

We used 216 features in total in this research, 120 from texture analysis and 96 from color analysis. We calculated 12 GLCMs for a full image and an image with green pixels removed. We used four different distances (1, 3, 10, and 20 pixels) as well as three different angles (0, \( \pi/4 \), and \( \pi/2 \)). We estimated five features for each GLCM (correlation, contrast, energy, homogeneity and dissimilarity). Only full photos were used to determine color characteristics. We employed 18 features in total, including 6 characteristics per color channel (mean, standard deviation, kurtosis, skew, entropy, and RMS). We also created a histogram with 26 buckets per channel and used pixel counts per bucket as features, yielding 78 features when multiplied by three channels.

C. Support Vector Machines
SVM is a supervised learning technique that may be used to solve problems like classification and regression. In the feature space, classification is done by defining a separating hyperplane. It conducts linear classification on two classes in its original form.

Figure 3: Example of two leaf images (top: healthy, bottom: diseased). From left to right: Full image, GLCM calculated on a full image, image with removed green pixels, GLCM calculated on image with removed green pixels.
It can also conduct non-linear classification using kernels. Kernels allow for highly non-linear hyperplanes by efficiently transforming the original feature space into a high-dimensional or infinite-dimensional feature space. SVM can fit extremely complicated datasets while having good generalization properties [6]. One-vs-all or one-vs-one techniques can be used to perform multiclass classification using SVM. The one-vs-all strategy trains N classifiers (N being the number of classes), each of which evaluates positive examples from one class and negative examples from all others. The one-vs-one strategy trains N(N-1)/2 binary classifiers and uses max-wins voting to decide the winner [10]. We tested with several configurations and discovered that utilizing the radial basis function kernel and the regularization value C=100 yielded the best results. A one-vs-all strategy was employed. On the test set, the accuracy achieved was 91.74 percent.

D. k-Nearest Neighbors
The k-NN [7] algorithm is a relatively simple classification algorithm. It’s non-parametric (there aren’t a set number of parameters) and lazy learning (there isn’t a training phase). The premise behind k-NN is that in the feature space, most samples from the same class are close to each other. When choosing the sample’s class, k-NN will look at its k closest neighbors and use the simple majority rule to determine which class it belongs to. Smaller k numbers allow for more nonlinearity, but they are more sensitive to outliers. High k values provide strong generalization, but they don’t fit complex limits. The best value for parameter k is found by trial and error. Small values of k were found to produce the best results for this dataset. The accuracy does not change much when k is changed from 1 to 9, with the best result being 78.06 percent, which is substantially lower than the SVM. In this study, we used k=5.

E. Fully Connected Neural Network
The simplest sort of artificial neural network is the FCNN. It’s a supervised learning approach for modelling extremely nonlinear functions. It does not converge to the global optimum like SVM and k-NN, but when properly configured, it usually produces acceptable results. Important neural network configuration parameters are:

- Number of hidden layers
- Activation function
- Number of neurons per layer
- Regularization methods
- Optimization method

We utilized an FCNN with four hidden layers of 300, 200, 100, and 50 neurons per layer in this paper. In buried layers, the activation function is a rectified linear unit (ReLU), with a SoftMax in the output layer [8]. With a regularization parameter of 0.3, we employed L2 regularization. The Adam optimizer was used with default parameters. On the test set, this setup provided an accuracy of 91.46 percent.

VI. DEEP LEARNING
Today’s artificial intelligence (AI) is largely built on this class of algorithms. Given enough data, deep learning algorithms have been demonstrated to be capable of learning exceedingly complicated patterns. A key advantage of DL algorithms is feature learning, in addition to the fact that they can fit incredibly complex models. DL models are fed raw data and are responsible for learning relevant features, so there is no need for feature engineering. Convolutional networks (CNN) are commonly utilized to solve picture recognition difficulties. In this research, we employed a Google Net [9] model with parameter configuration described in [3] to compare with traditional models.

The model was employed with weights that were pre-trained on the ImageNet [11] dataset. The following are the parameters that were used:

- Optimizer: Stochastic Gradient Descent
- Learning rate: 0.005
- Momentum: 0.9
- Weight decay: 0.0005
- Batch size: 24
- Number of epochs: 10

VII. EXPERIMENTAL RESULTS
We compared three traditional algorithms (SVM, k NN, FCNN) and one deep learning algorithm (DL) (CNN). Sections III and IV provided a detailed overview of the parameters employed. The classical algorithms were implemented in Python, utilizing the scikit-learn package for the classical algorithms and Keras on top of Tensor Flow for the deep learning model. The code was run on the Google Colab platform, which provides free CPU and GPU
resources. Traditional algorithms were trained on the CPU, while the DL model was trained on the GPU. In an 80-20 split, data was separated into training and test sets (80 percent of data was used for training, 20 percent for testing). We employed accuracy, precision, recall, and F1 score as measures. The precision, recall, and F1 score are all averaged together. Table 1 shows the results.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy</th>
<th>F1 score</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>0.917</td>
<td>0.894</td>
<td>0.903</td>
<td>0.89</td>
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<tr>
<td>k-NN</td>
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<td>FCNN</td>
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<tr>
<td>CNN</td>
<td>0.993</td>
<td>0.99</td>
<td>0.991</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Table 1: Metrics of tested algorithms

We can see that k-NN scores significantly lower than the other options. SVM and FCNN produce equivalent outcomes, albeit they are still significantly inferior to CNN, which has been proved to produce the best results by far. CNN has a low error rate of less than 1%, compared to 8-9 percent for SVM and FCNN, and more than 20% for k-NN.

VIII. CONCLUSION

The superiority of the DL approach over traditional ML algorithms is demonstrated in this research. The DL is the way to go for picture classification problems with somewhat large datasets, based on both the simplicity of the approach and the acquired accuracy. Trying to improve the DL method’s results on the same dataset would be pointless because the method’s accuracy is already very good. Expanding the dataset with more diverse photos collected from other sources, in order to allow the DL model to generalize better, could be done in the future. Although the ML algorithms studied were relatively accurate, their error rates were still an order of magnitude greater than the DL model. Experimenting with alternative algorithms and increasing the characteristics, which are most likely the limiting element of this strategy, can help improve the accuracy of the traditional approach.

IX. FUTURE WORK

We want to expand the project in the future so that it can display an image of a diseased plant together with the plant and disease names.

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