ISSN:0976-0172

Journal of Bioscience And Technology
www.jbstonline.com

Deep Learning vs. Classical Machine Learning Algorithms for Image-Based Plant Disease Detection

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Article Info

Received: 30-04-2025 Revised: 16-06-2025 Accepted: 28-06-2025

Abstract

A parallel rise in food production is necessary to meet the demands of a rapidly expanding human population. Contagious illnesses may wreak havoc on agricultural productivity and sometimes wipe out whole harvests. This highlights the critical importance of early illness detection and preventive efforts. Laboratory testing and professional human judgment constitute the backbone of conventional wisdom, yet these resources are often out of reach for people in the developing countries. Automated picture analysis has recently been used by scientists to detect agricultural diseases, since cellphones are becoming more common even in rural regions. The most current findings in this area are presented in this study, which also compares the deep learning method to the traditional machine learning techniques.

Keywords

Artificial intelligence, Agricultural pests, and Neural Networks.

I. INTRODUCTION

The need for food production is rising in tandem with the ever-increasing human population. In 2050, the United Nations projects that the global population will reach 9.7 billion, an increase of 2 billion from the current estimate. It is reasonable to assume that reducing food waste in the world's poorest nations should be a top priority, given that these nations will experience the lion's share of population growth (an estimated 80% rise in the next 30 years) and food shortages. Worldwide, yield loss is thought to reach 20–40 percent [2], with many farms experiencing a complete loss. The conventional wisdom is that in order to identify illnesses, specialists must physically examine plants. This procedure must be ongoing, which may be prohibitively costly for big farms and beyond of reach for many small-scale farmers in rural regions. For this reason, there have been many efforts in the past few decades to automate the process of illness identification. The use of hyperspectral imaging is one strategy that stands out. For the purpose of monitoring expansive regions, hyperspectral pictures are often captured by means of aerial imaging equipment or satellites. The method has a few drawbacks, including a limited sample size, high dimensionality, and an exceedingly high equipment cost.they aren't good candidates for ML analysis. The most prevalent technique right now is RGB image analysis, which is driven by recent advances in computer vision and the availability of affordable technology. Another reason to look into RGB photos is that these solutions might potentially reach even the most remote rural places, thanks to how common smartphones are now. Deep learning (DL) and traditional ML algorithms can both assess

ISSN:0976-0172

Journal of Bioscience And Technology
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RGB photos. Feature extraction and picture pre-processing are the backbone of traditional approaches that feed into ML algorithms. Some of the most common algorithms used in machine learning include support vector machines, decision trees, random forests, k-nearest neighbors, and fully connected neural networks. For picture classification tasks, researchers have turned almost completely to DL approaches in recent years. The rationale for this is because, when presented with a sufficiently enough dataset, they routinely surpass conventional methods and don't need the creation of custom features for implementation. In this research, we examine the instance of plant disease classification and contrast the DL method with traditional ML techniques.

II. DATASET

The PlantVillage Dataset is cited as follows: [3]. The photos are captured of plant leaves in a controlled setting. The 54, 306 photos include 14 plant species, which are categorized into 38 different groups based on the species and illness they represent. This dataset contains the following species: grapes, oranges, peaches, bell peppers, potatoes, raspberries, soybeans, squash, tomatoes, blueberries, cherries, corn, and grapes. In addition to pictures of healthy plants from 12 species, this collection contains photographs of 17 fungal illnesses, 4 bacterial diseases, 2 viral infections, 2 mold diseases, and 1 mite disease. The images were captured with a regular digital camera, outdoors, under varying weather conditions, and from various sources, which added diversity to the collection. This dataset is well-suited for applying ML algorithms, particularly DL ones, because to its large number of samples and variety of disorders. A major drawback of this dataset is that the photographic settings were drastically altered from what they would have been in the field since individual leaves were chopped and placed against a consistent backdrop. Figure 1 shows that the picture distribution is not uniform and that there are 150–5500 samples per class. Additionally, there were complaints about a substantial amount of samples that were mislabeled in [4]. The collection contains a variety of picture types, including color, grayscale, and segmented

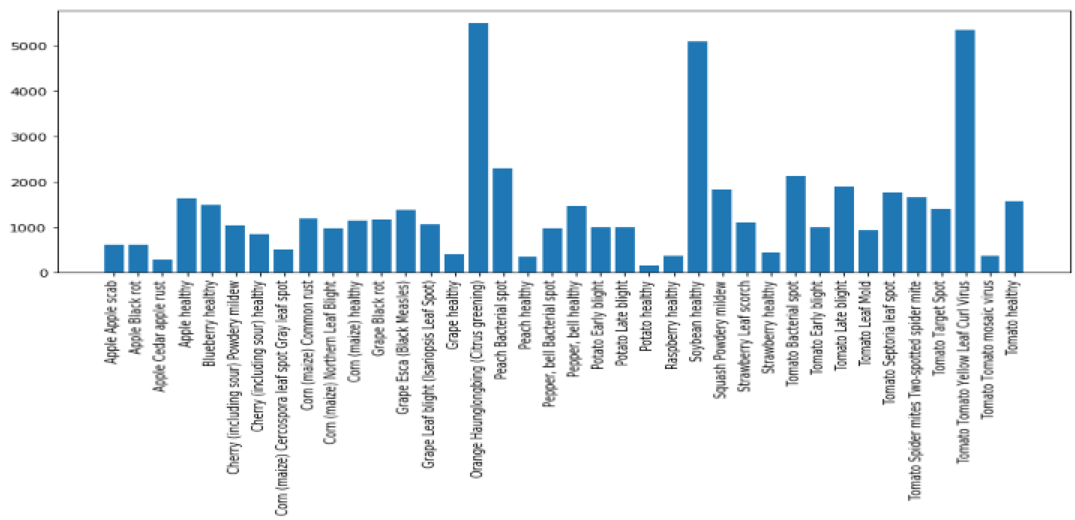

Figure 1: Number of samples per class

pictures in which the backdrop is obscured. The article makes use of segmented photos.

ISSN:0976-0172

S. Venkateswar Rao, JBio sci Tech, Vol 13(2),2025, 01-06

Journal of Bioscience And Technology
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III. CLASSICAL ML APPROACH

There are certain pre-processing processes that must be followed while using classical algorithms. Figure 2 provides an overview.

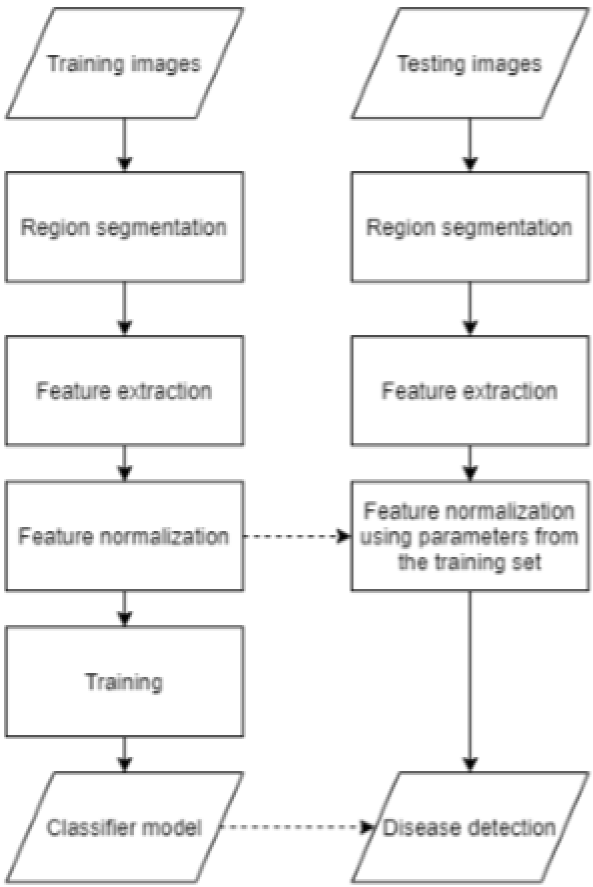

Figure 2: Flowchart of the basic training and testing steps

Part A: Segmenting regions Scaling pictures to uniform dimensions, removing the background, and artifacts are common preparation procedures in image classification. We skipped over these stages as the PlantVillage dataset already has scaled and segmented pictures. In order to isolate potentially diseased leaf regions, we performed further segmentation on these pictures during preprocessing. This included deleting any pixels with green channel values greater than the red and blue ones. The pictures that have been segmented and those that have had their green pixels removed are shown in Figure 3. B. Extracting features Feature selection is both the most crucial and most challenging aspect of ML algorithm development. Expertise in the relevant subject and thorough investigation are necessary for feature selection. Utilizing texture characteristics derived from the grey level co-occurrence matrix (GLCM) [5] and general color statistical features derived from histogram analysis of the whole picture,

ISSN:0976-0172

Journal of Bioscience And Technology
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we have conducted this study on both full-image and images with green pixels removed images. The GLCM expresses the likelihood of two pixel values, i and j, existing on a distance d and at an angle θ from one other, which is a spatial connection of nearby pixels. The matrix is described as a N×N grid, where N is the count of unique pixel values, and G(i,j) is the count of occurrences of pixel j at distance d and angle θ from pixel i. The GLCM may be used to extract texture characteristics such as similarity, homogeneity, contrast, energy, and correlation. In order to get a basic idea of the image's color statistics, color characteristics are derived by extracting statistical features from the histograms of the images. A total of 216 characteristics, 120 from texture analysis and 96 from color analysis, were used in this research. For the whole picture and the image with the green pixels deleted, we have computed 12 GLCMs. Four distances (1, 3, 10, and 20 pixels) and three angles (0, π/4, π/2) have been used. Five features—correlation, contrast, energy, homogeneity, and dissimilarity—have been computed for every GLCM. Full photos were the only ones for which color characteristics were computed. We used a total of 18 features, with 6 characteristics per color channel. These features included mean, standard deviation, kurtosis, skew, entropy, and RMS. Additionally, we computed a histogram using 26

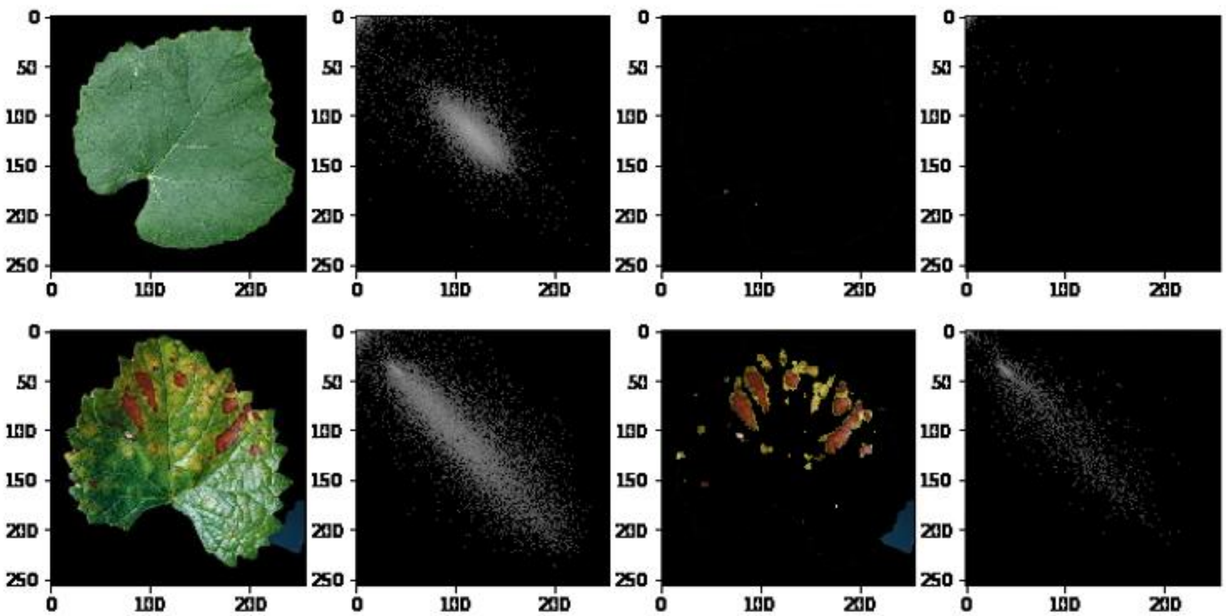

Figure 3: Example of two leaf images (top: healthy, bottom: diseased). From left to right: Full image, GLCM calculated on a full image, image with removed green pixels, GLCM calculated on image with removed green pixels.

we utilized the pixel count per bucket as a feature and multiplied it by three channels, which gave us 78 features, with buckets per channel. Subheading: C. SVMs Classification and regression issues are well-suited to SVM, a supervised learning method. In order to do classification, a separating hyperplane is defined in the feature space. There was an earlier version that used linear classification on only two categories. It is also capable of nonlinear classification using kernels. To efficiently generate extremely non-linear hyperplanes, kernels are used to turn the original feature space into a high-dimensional or infinite-dimensional feature space. In addition to having strong generalizability features, SVM is able to fit very complicated datasets [6]. Both one-versus-all and one-versus-one procedures may be used to perform multiclass classification using SVM. Training N classifiers (where N is the number of classes) in a one-vs-all fashion means that each classifier will only accept examples that belong to its own class and will reject any examples from other classes. The one-vs-one method uses max-wins voting to choose a victor and trains N(N-1)/2 binary classifiers [10]. Using the radial basis function kernel with the regularization parameter set to 100 yielded the best results among the many combinations we tested. We used a one-versus-all strategy. D. k-Nearest Neighbours attained an accuracy of 91.74% on the test set. When faced with a classification challenge, many turn to the straightforward k-NN [7] technique. It lacks a training phase and is lazy learning, meaning it does not have a set amount of parameters. k-NN is based on the premise that the majority of samples belonging to the same class are near one other in the feature space. By using the basic majority rule, k-NN will examine its k nearest neighbors and determine the sample's class. While smaller values of k make non-linearity more apparent, they also make them more susceptible to outliers. Good generalization is achieved with high values of k, but complicated boundary fitting fails. Experimental results are used to find the optimal value of the parameter k. It was found that modest values of k produced the best results for this dataset. The accuracy is very constant over the range of k=1–9, with the highest result falling far below the SVM at 78.06%. The task was conducted using k=5. Section E. Highly Connected Neural Networks First-class neural networks (FCNNs) are the most basic kind of ANNs. It can model very non-linear functions; it is a supervised learning method. It doesn't converge to the global optimum as SVM and k-NN do, but it typically produces adequate results when set up correctly. The activation function, number of neurons per layer, regularization technique, and optimization method are important factors to consider while configuring a neural network. Other important parameters include the number of hidden layers. We used a four-hidden-layer FCNN in this study; each layer has 300, 200, 100, and 50 neurons. A rectified linear unit (ReLU) activation function is used in hidden layers, while a softmax is used in the output layer [8]. Our regularization value was set at 0.3 and we used L2 regularization. The default settings were used by the Adam optimizer. With this setup, we achieved a test set accuracy of 91.46 percent.

IV. DEEP LEARNING

Deep learning (DL) is an ML algorithm class that learns features hierarchically using many layers. Although DL algorithms come in many forms, artificial neural networks constitute the backbone of the majority of them. The most cutting-edge AI systems nowadays rely heavily on this category of algorithms. Given sufficient data, DL models have shown the ability to learn very complicated patterns. One major benefit of DL algorithms is feature learning, in addition to their ability to fit very complicated models. Because DL models learn the right features from raw data, feature engineering is unnecessary when using DL. The majority of image recognition issues are addressed by convolutional neural networks (CNN). A GoogLeNet [9] model with the parameter configuration reported in [3] was used for comparison with classical models in this work. Our model was trained using weights extracted from the ImageNet [11] dataset. This is what the parameters are: Stochastic Gradient Descent is the optimizer. • 24 batch sizes • 10 epochs • 0.005 learning rate • 0.9 momentum • 0.0005 weight decay With a 99.32% accuracy rate, our DL model far outperforms traditional techniques and converges in only 10 epochs.

V. EXPERIMENTAL RESULTS

Three traditional algorithms—SVM, kNN, and FCNN—and one deep learning algorithm—CNN—have been evaluated. In parts III and IV, the parameters that were employed were described in detail. Python was used for the implementation, with the scikit-learn package providing support for classical techniques and Keras atop TensorFlow for the DL model. The Google Colab platform, which provides free access to CPU and GPU resources, was used to run the code. Classical methods were trained on the CPU, while the DL model was trained on the GPU. The data was split into two sets: one for training and one for testing. The ratio of training to testing was 80:20. Precision, accuracy, recall, and F1 score were the measurements that were used. We take a macro average of the precision, recall, and F1 score. Table 1 displays the results:

	Accuracy	F1 score	Precision	Recall
SVM	0.917	0.894	0.903	0.89
k-NN	0.78	0.727	0.742	0.724
FCNN	0.914	0.892	0.899	0.892
CNN	0.993	0.99	0.991	0.99

ISSN:0976-0172

Journal of Bioscience And Technology
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Table 1: Metrics of tested algorithms

The results show that k-NN is much worse than the alternatives. CNN produced the best results, by a wide margin, whereas SVM and FCNN provide outcomes that are equivalent but far lower. In contrast to SVM and FCNN, which had error rates of 8–9% and over 20%, respectively, CNN achieved an error rate of less than 1%.

VI. CONCLUSION

Compared to traditional ML algorithms, the DL approach is clearly superior, as shown in this study. In order to solve picture classification issues with somewhat big datasets, DL is the way to go because of how simple it is and how accurate it is. The DL method's attained accuracy is already quite good, thus there's little need in attempting to increase its results on the same dataset. Adding additional varied photos from other sources to the dataset would improve the DL model's ability to generalize, which might lead to further work with the model. Although the targeted ML algorithms outperformed the DL model in terms of accuracy, their error rates were still much higher. It is probable that the features are the limiting element of the traditional technique, thus next study might include experimenting with other algorithms and enhancing them to make this approach more accurate.

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