Machine Learning Data Fusion for Plant Disease Detection and Classification

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Abstract

It is crucial to quickly identify plant diseases since they impede the development of affected plants. Despite the widespread use of Machine Learning (ML) models for this purpose, the recent advances in a subset of ML known as Deep Learning (DL) suggest that this field of study has much room for improvement in terms of detection and classification accuracy. To identify and categorize plant diseases, a wide variety of established and customized DL architectures are deployed with several visual analysis methods. In this study, we use deep learning techniques to create a model for a convolutional neural network that can identify and diagnose plant diseases using very basic photos of healthy and sick plant leaves. The models were trained using an open library of 20639 photos that included both healthy and diseased plants across 15 different classifications. Some model architectures were trained, with the highest performance obtaining a success rate of 97.70% in detecting the correct [plant, illness] pair (or healthy plant). Due to its impressive success rate, the model is a valuable advising or early warning tool, and its technique might be developed to help an integrated plant disease diagnosis system function in actual production settings.

Keywords: Data Fusion; Deep Learning; Machine Learning; Image Data Processing; Deep Fusion

1. Introduction

The FAO cites insect infestations and plant diseases as two of the primary factors in declining food production and quality. Plant diseases change with the seasons because of factors including the kind of pathogens present, the weather, and the crops being grown. Diagnosing plant diseases by visually inspecting the signs on their leaves involves a deep level of analysis. Due to the complexity and sheer volume of crop species and their preexisting phytopathological issues, even experienced horticulturalists and plant pathology occasionally make an inaccurate diagnosis of specific ailments.

An increasing number of farms are realizing the potential of autonomous plant disease identification tools as reliable data points for informing management decisions. This is particularly the case in remote areas with limited access to specialized technical help, as well as on big estates where constant on-site monitoring is impossible[1]. Many problems, however, remain unanswered since no viable strategies have yet been developed. Deep learning approaches are emerging as the preferred approach to tackling some of these difficulties[2].

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To create a computational model that is strikingly similar to the biological processes of humans, the Deep Learning (DL) technique was first presented in 1943 when threshold logic was created. Research in this area is ongoing and may be roughly separated into two time periods: 1943–2006 and 2012–present. Backpropagation, chain rule, Neocognitron, handwritten text recognition (LeNET architecture), and the solution to the training issue were all advancements that occurred during the first stage[3], [4]. In the later stages, however, state-of-the-art algorithms/architectures were developed for a wide variety of uses, such as autonomous vehicles, the medical field, text recognition, earthquake predictions, advertising, financial applications, and image recognition. When it comes to object recognition, the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) was won by the AlexNet architecture, which is widely regarded as a major advancement in the area of DL[5]–[7]. Almost immediately, new architectures were developed to plug the gaps that had been found. Several performance indicators were used in the assessment of these algorithmic frameworks. Most often used are the top-1% and top-5% error, precision and recall, F1 score, training/validation accuracy and loss, and classification accuracy (CA)[8]–[16]. From data collection to final graphical mappings, several processes are needed for putting DL models into action. Figure 1 shows the flow diagram[17]–[19].

Multiple ambient, plant canopy, and leaf indices derived from remote sensing photography, as well as Internet of Things (IoT) sensors, may be given to the agricultural field. Because of the heterogeneity of the retrieved data, data fusion methods are necessary to compile the collected information into a coherent whole that can be used to analyze crop growth and the onset of disease. There have been major developments in ML-based data fusion, which, if used with information from the agricultural industry, would have a substantial impact on plant protection, particularly in the areas of illness and early disease identification. Therefore, several fusion techniques using a wide assortment of sensors and sensing have been employed in the agricultural sector[20]–[22].

In this study, we use Convolutional Neural Networks (CNNs), a fundamental deep learning method. When it comes to modeling complicated processes and conducting pattern identification in applications with a vast quantity of data, such as picture pattern recognition, CNNs are one of the most powerful approaches. In 2015, Lee et al. proposed a Convolutional Neural Networks (CNNs) system for automatic plant detection using photos of leaves. In 2016, Grinblat et al. successfully used a neural network they designed to distinguish between three distinct species of legumes based on the morphological patterns of their leaves veins, despite the network's apparent simplicity. Using an accessible library of leaf pictures from 14 distinct plants, Mohanty et al. evaluated two well-known and established designs of CNNs for the diagnosis of 26 plant diseases. The success percentage of their automated identification system reached 99.35%, which is highly encouraging. One major issue, however, was that all of the photographs depicted either laboratory or other controlled experimental settings, rather than actual outside growing circumstances. Using a comparable quantity of publicly accessible Internet data, Sladojevic et al. devised a similar system for plant disease diagnosis from leaf photos. This time, however, they focused on a smaller number of illnesses (13) and different species (5). Depending on the test data, their models' success percentages ranged from 91% to 98%.[22]–[28]

To create an automated system for detecting and diagnosing plant diseases from basic photos of healthy and sick leaves, this study trained and evaluated many different CNN architectures. Images were included in the collection that was taken in both controlled lab settings and in the field under natural growing circumstances. In contrast to shallow techniques that learn with less data but are crop-specific, the proposed deep learning methodology may discover more generic answers.

Following this introduction, the study is split into three sections: Section 2, describes both well-established and cutting-edge DL architectures and mapping/visualization approaches for identifying plant diseases; Section 3, provides additional information about Hyperspectral Imaging with DL models; section provides the results and discussion of this study, and Section 5, which concludes the review and provides future recommendations for achieving further improvements in the aforementioned areas.

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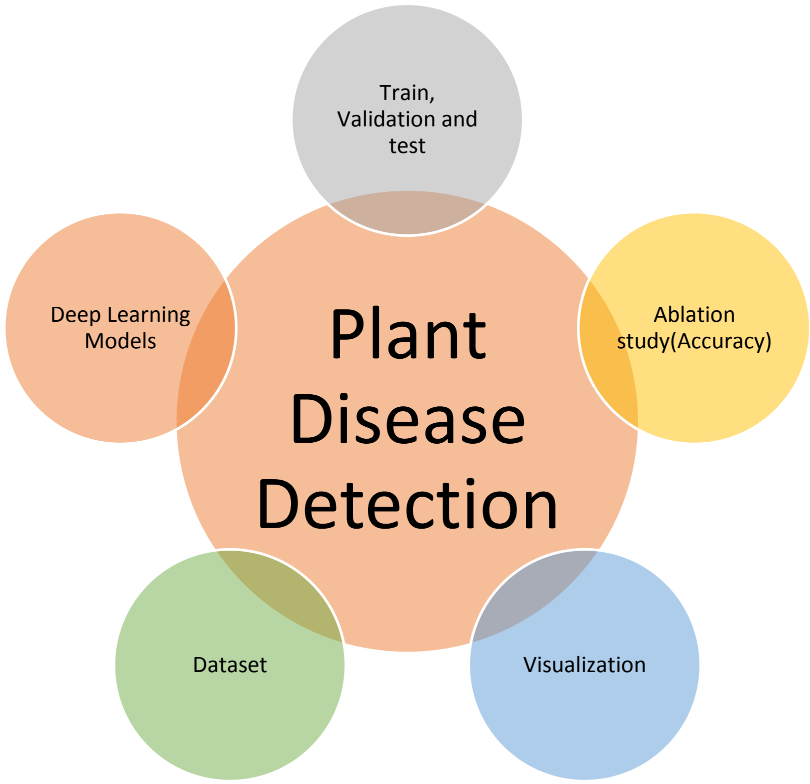

Figure 1: Flowchart of a DL.

Flowchart of a DL Deployment Before beginning to analyze the data, the dataset is often divided in half, with the first half serving as the training and testing set and the second half as the test set. After DL networks are constructed from zero or via transfer learning, training/validation charts are made to highlight their significance. Next, images are detected, localized, and classified using visualization methods and mappings, and finally, evaluation metrics such as (accuracy, precision, recall, etc.) are evaluated.

2. Plant Disease Detection with DL Architectures

2.1 CNN Model

The neurons and synapses in artificial neural networks are mathematical representations of the basic principles by which the brain functions. Its capacity to be taught using supervised learning is its defining feature. In this procedure, neural networks are "trained" to simulate a given system by feeding them with examples of inputs and outputs that already exist for that system. In contrast to classic artificial neural networks, convolutional neural networks are primarily concerned with applications that have repeated patterns in many regions of the modeling space, most notably, the ability to recognize images. The fundamental difference between these and traditional feedforward neural networks is that, because of their layered construction, fewer main members (artificial neurons) are required. Several CNN baseline designs have been created for picture re- cognition applications and have been effectively used to challenge visual imaging challenges.

2.2 Dataset and Model Steps

The CNN models were trained and tested using an open database including 20,639 images of plant leaves, both healthy and sick. Hughes and Salathé describe an early version of the database with fewer photos. The 15 classes included in the database are characterized as combinations of plant and illness, with some classes also including disease-free plants. There are 25 distinct types of plants represented among these 15 categories, some of which are healthy and others not. Two

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representative photos captured in a controlled environment and two captured in natural light are shown in Figures. 2 to 6, representing a random sample of the class. Several factors, including a greater number of leaves and other plant components, extraneous items (such as shoes), varying ground textures, shading effects, etc., contribute to the greater complexity of the later photos. Table 1 shows the number of images belonging to 15 classes.

A total of 20639 photos were taken from the database and split into two datasets at random: a training set with 80% of the pictures and additional measurements with 20%. Through 80/20 splits are common in neural network implementations, similar splits (e.g., 70/30) are unlikely to have a major impact on the quality of the resulting models. A total of 16511 photos were used to teach the Cnn architectures, while the other 4128 were kept to test the accuracy with which the models could classify new, "unseen" pictures. Both the training and testing samples had the same ratio of photos captured under controlled laboratory circumstances to those captured in natural settings. To generate pseudorandom numbers that were distributed evenly throughout the two datasets, a python script was written. These numbers were used to choose photographs at random.

Besides this, another strategy for developing the training and testing data was investigated, which included pre-processing the photos by reducing their size and cropping them to 256 * 256 pixels Using 3 channels and the same 80/20 split between training and testing. There is evidence from prior literature suggesting that this approach does not improve the deep learning networks' final classification accuracy in similar settings, hence we did not investigate utilizing grayscale versions of the photos for training. The same holds for leaf segmentation from picture backgrounds, hence this extra step was also disregarded. This is true because CNNs and other deep learning systems can tell which aspects of a picture collection are most relevant, and which are less so, and may choose to ignore the less relevant ones. Avoiding the need for an extra step segmentation of the items of interest which may become troublesome in complicated pictures like the field images used in this application, is a major benefit. Figures 2 to 6 show the images of datasets

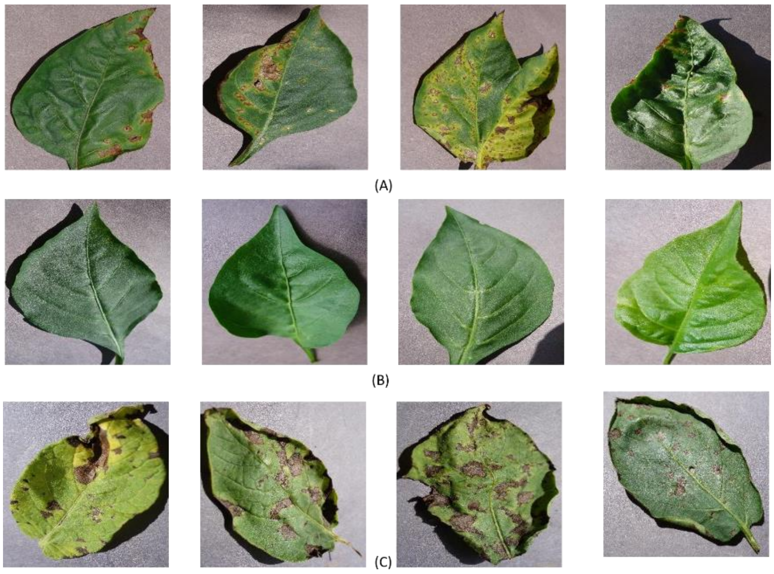

Figure 2: A: Pepper bell Bacterial spot, B: Pepper bell healthy, C: Potato Early blight

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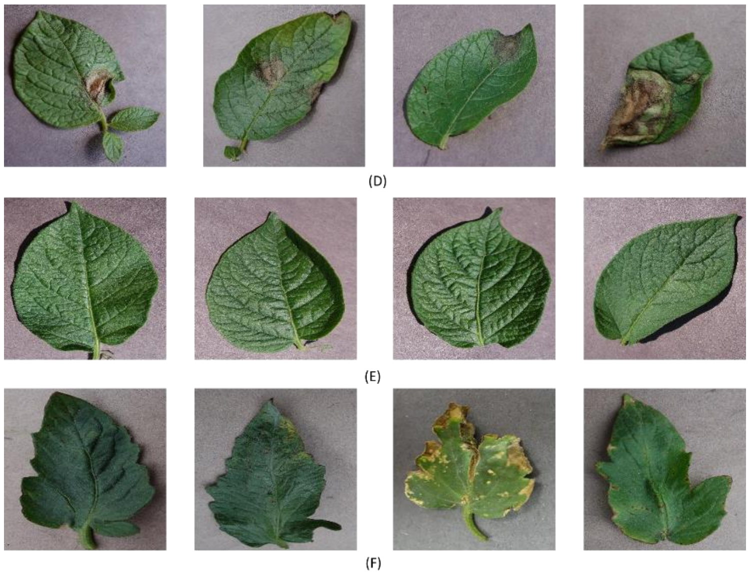

Figure 3: D: Potato Late blight, E: Potato healthy, F: Tomato Bacterial spot

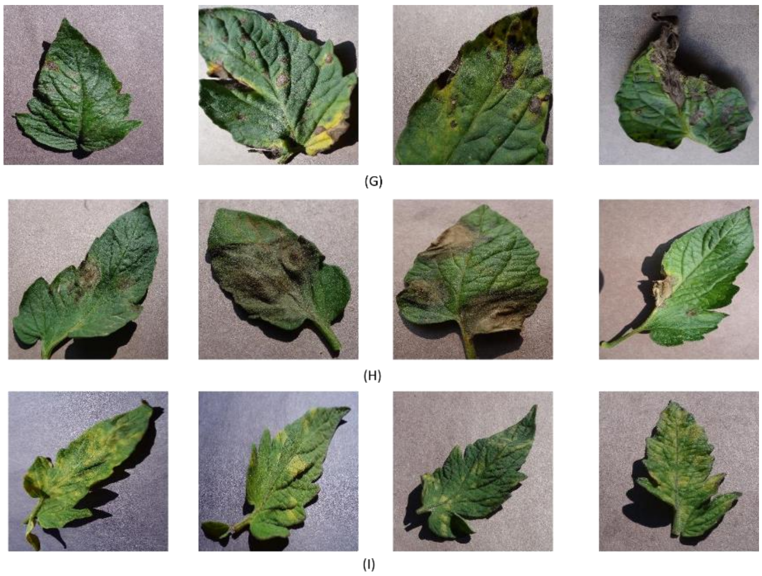

Figure 4: G: Tomato Early blight, H: Tomato Late blight, I: Tomato Leaf Mold

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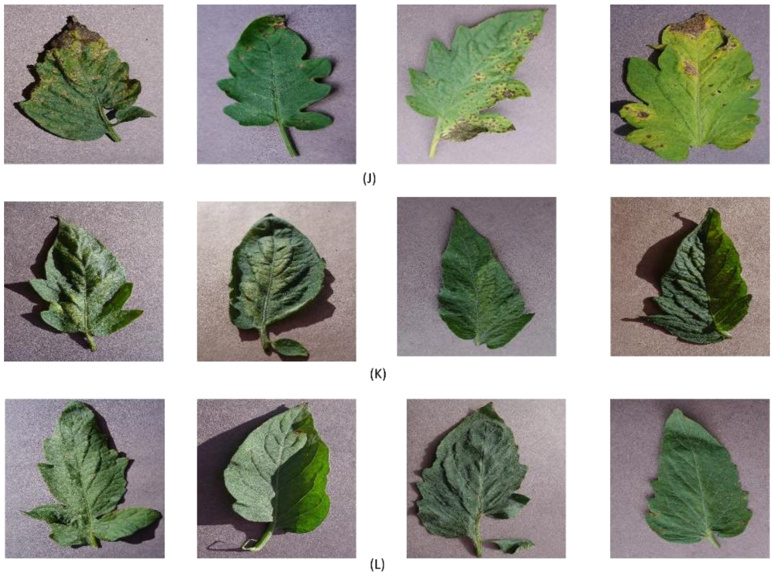

Figure 5: J: Tomato Septoria leaf spot, K: Tomato Spider mites Two-spotted spider mite, L: Tomato Target Spot.

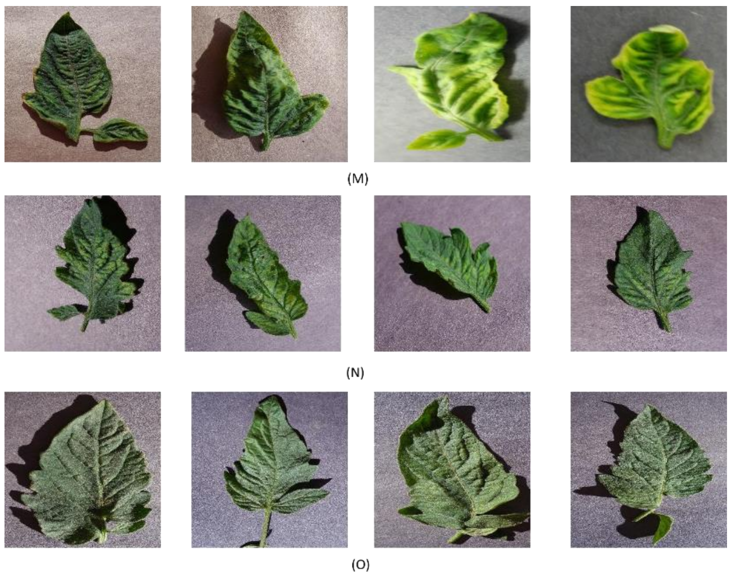

Figure 6: M: Tomato Yellow Leaf Curl Virus, N: Tomato mosaic virus, O: Tomato healthy

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Table 1: The number of images belongs to 15 classes

Class	Number of Images
Pepper bell Bacterial spot	997
Pepper bell healthy	1478
Potato Early blight	1000
Potato Late blight	1000
Potato healthy	152
Tomato Bacterial spot	2127
Tomato Early blight	1000
Tomato Late blight	1909
Tomato Leaf Mold	952
Tomato Septoria leaf spot	1771
Tomato Spider mites Two spotted spider mite	1676
Tomato Target Spot	1404
Tomato Yellow Leaf Curl Virus	3209
Tomato mosaic virus	373
Tomato healthy	1591

3. Data Fusion

Given the variety of data sources at our disposal, it makes sense to integrate them for enhanced illness detection. The use of multimodal fusion in the diagnosis of illness is still a topic of active research. In reality, scientists have begun to recognize the significance of integrating disparate data sets collected by a variety of sensors. However, much work is needed to combine complex fusion methods with multimodal information. Because of this, we can learn more about how crops act, which will lead to more accurate forecasts. Integrating information from several sensors allows for more precise and efficient plant prediction.

Data fusion is the process of integrating information and data from numerous sources simultaneously to improve performance beyond what could be achieved by using any one source alone. This phenomenon is commonly linked to the need of sensing several environmental factors. Because it involves combining disparate data types (images, signals, time series, etc.), multimodal data fusion is a difficult process. Historically, probabilistic fusion approaches have been the gold standard, but recent studies have shown that machine learning techniques may improve prediction accuracy for fusion. In this article, we examine the many data fusion applications in agriculture that make use of machine learning, including measurement fusion, feature fusion, decision fusion, hybrid fusion, and tensor fusion. Finally, the key obstacles to implementing data fusion in agriculture will be discussed.

By integrating feature vectors, feature fusion incorporates heterogeneous data from several sources. This is accomplished by combining the findings of early fusion with separate unimodal predictors. In, four different forms of data were used as inputs to deep fusion designs for detecting flaws in a planetary gearbox. As part of the multimodal data fusion process, deep convolutional neural networks (DCNNs) were implemented at various stages. After the raw data was extracted, we fused the features at the feature level with the features we had learned from the data. Feature-learning DCNNs were applied to each data type, and the resulting features were subsequently extracted. Finally, another DCNN was given the merged set of features to perform feature-level fusion categorization.

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Hybrid fusion involves the merging of data from many sources. Object recognition in dynamic settings, suggests a hybrid strategy in which several CNN classifiers are combined. RGB, depth, and optical flow were employed as the three input modalities. To combine the results from several expert network models into a single prediction, the CifarNet architecture was developed as a unifying principle. The term "Mixture of Deep Experts" describes this strategy (MoDE).

4. Results

Table 2 displays the training parameters used to develop the various CNN models mentioned in Section 2. These parameters were found to provide the greatest training outcomes after extensive experimentation. Starting at 0.001 throughout 25 epochs, the learning rate was lowered using a specified annealing schedule, halving or halving every 25 epochs until it reached 0.0001. All models were perfect on the training set, thus comparisons were made based on how they fared on the testing data.

Testing rates of success for model classification are shown in Table 3 for the two basic training/testing procedures of the 15 categories (i.e., training/testing in an 80/20 proportion, using the original pictures in the first instance, and the pre-processed, bottom, squared images in the second case). One statistic offered is the proportion of properly labeled photos (plant vs. illness) as a function of the total amount of photographs (ii) the training failure rate, and (iii) the model summary error (average loss per batch, overall batches in the testing set)

Table 2: Parameters of CNN model

Parameter	Value
Epoch	25
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Image Size	256*256*3
Weight decay	0.001

Table 3. Accuracy for different epoch

Epoch	Accuracy	Loss	Validation Accuracy	Validation Loss
10	96%	0.1	89.5%	1.05
20	98%	0.049	90.42%	0.87
25	98.26%	0.046	97.90%	0.11

All of the results from the various classifiers are summed together in the confusion matrix. The TP, TN, FP, and FN values for each class are represented in the contingency table of something like the classification method. One common method of assessing a learning algorithm's efficacy is its area underneath the receiver operational characteristic (AUC-ROC) curve. The distinction between the true positives (TPR) and the false positives rate (FPR) is shown graphically in the area under the receiver operating characteristic.

$$TPR = \frac{TP}{TP + FN}$$

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$$FPR = \frac{FP}{FP + TN}$$

$$Classification\ accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

According to the findings of the comparisons, the suggested 14-DCNN has better accuracy, clarity, recall, and F1 scores than the AlexNet, Inception-v3-Net, ResNet-50, and VGG16Net. Table 3 further illustrates the difficulty of the suggested and other classification techniques approaches. Figure 7 shows the performance analysis. Table 4 shows the comparison between previous work.

Table 4: Comparison of other models

	AlexNet	Inception-v3-Net	ResNet-50	VGG16Net	14-DCNN
No. of Parameters	44,752,739	24,937,283	26,722,211	39,443,043	17,928,571
Model Size (MB)	133	92	98	128	37

Table 5: The accuracy of previous work.

Author(s) name and year	Proposed approach	Testing accuracy
[23]	Convolutional Encoder Network	86.78%
[24]	ResNet-152	99.2%
[25]	VGG-19 + SVM	97.8%
[26]	ResNet-50 + SVM	98%
[27]	VGG-19	98%
[28]	VGGNet	99.5%
[20]	GoogLeNet	99.3%
Proposed approach	CNN	98.38%

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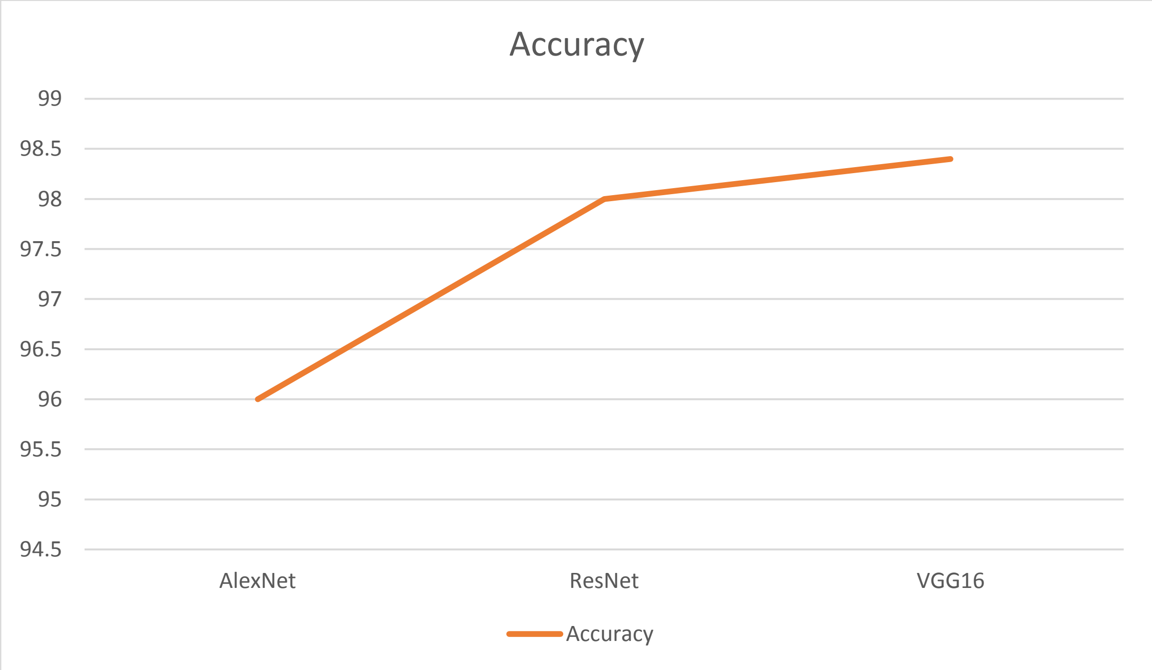

Figure 7: The performance analysis

5. Conclusion

In this study, we used basic leaf photos from healthy and ill plants to train deep learning models to distinguish between the two. To train the models, we used a publicly accessible library of 20639 images captured both in lab settings and in actual agricultural areas. There are 25 plant species represented in a total of 15 classifications [plant, illness] in the data, some of which are healthy. The convolutional neural network was the most effective model architecture, with a 97.90% accuracy rate in the categorization of 4128 plant leaves photos (testing set) that had never been viewed by the model before. This remarkable outcome proves the efficacy of CNN in automating the recognition and diagnosis of crop diseases via the analysis of simple photographs of plants. The findings also highlighted the significance of including photographs taken in real-world situations (in the fields of agriculture) in the training data, implying that developers of these systems should prioritize increasing the proportion of such images.

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