Plant Disease Detection using Deep Learning

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Abstract: *India is a country where still 70% of people still are dependent on agriculture as their main source of income, being such a high populous country there is always increasing demand for food supplies. Farmers face approx. 30% losses every year due to crops being affected by some diseases or due to some natural calamity. From past as well as even today may farmers check for diseases in plants through naked eyes most of the time plant diseases on a leaf look the same which can lead to confusion on what kind of fertilizer should we used to overcome it. To overcome this problem, we have created a deep learning-based application to predict the diseases of the plants.*

***Key Words*: Deep learning, machine learning, convolutional neural network, plant diseases, Transfer Learning.**

1. Introduction:

Modern technologies have allowed human civilization to produce enough food to feed more than 7 billion people. However, food security is still threatened by a variety of factors such as climate change, pollinator decline, plant diseases, and others. Plant diseases not only pose a global threat to food security, but they can also have devastating consequences for smallholder farmers whose livelihoods depend on safe crops. Smallholder farmers produce more than 80% of agricultural output in the developing world, and reports of yield losses of more than 50% due to pests and diseases are common. Furthermore, the majority of hungry people (50 percent) live in smallholder farming households, making smallholder farmers especially vulnerable to pathogen-related disruptions in the food supply. Several initiatives have been introduced to avoid crop loss due to disease. In the last decade, integrated pest management (IPM) methods have gradually replaced historical approaches of widespread pesticide use. Regardless of strategy, correctly recognizing a disease when it first occurs is a critical step in disease management. Historically, agricultural extension organizations or other agencies, such as local plant clinics, have assisted in disease detection. Because of their processing ability, high-resolution screens, and comprehensive built-in collections of accessories, such as specialized HD cameras, smartphones, in particular, provide very novel approaches to assisting in disease identification. It is widely predicted that by 2020, there will be between 5 and 6 billion smartphones on the planet. By the end of 2015, 69 percent of the global population had access to mobile broadband coverage, with mobile broadband penetration reaching 47 percent in 2015, a 12-fold rise since 2007[6].

1.1 Introduction to machine learning:

Machine learning is the concept of employing algorithms to discover patterns and/or make predictions based on a set of data. There are numerous algorithms available, each with its own set of advantages and disadvantages, as well as varying degrees of complexity. These algorithms are simple to use and available in a variety of programming languages (including R and Python) with varying degrees of coding complexity. They may be able to replace the need for detailed coding instructions unique to your application with more general instructions.[2]

1.2 Introduction to Deep Learning:

Deep learning is a type of machine learning in which a model learns to perform classification tasks directly from images, text, or sound. Deep learning is usually implemented using neural network architecture. The term deep refers to the number of layers in the network—the more the layers, the deeper the network. Traditional neural networks contain only two or three layers, while deep networks can have hundreds.

A deep neural network combines multiple non-linear processing layers, using simple elements operating in parallel. It is inspired by the biological nervous system and consists of an input layer, several hidden layers, and an output layer. The layers are interconnected via nodes, or neurons, with each hidden layer using the output of the previous layer as its input.[1]

The recent advances in deep-learning technologies based on neural networks have led to the emergence of high-performance algorithms for interpreting images, such as object detection, semantic segmentation instance segmentation, and image generation. As neural networks can learn the high-dimensional hierarchical features of objects from large sets of training data, deep-learning algorithms can acquire a high generalization ability to recognize images, i.e., they can interpret images that they have not been shown before, which is one of the traits of artificial intelligence. Soon after the success of deep-learning algorithms in general scene recognition challenges, attempts at automation began for imaging tasks that are conducted by human experts, such as medical diagnosis and biological image analysis. However, despite significant advances in image recognition algorithms, the implementation of these tools for practical applications remains challenging because of the unique requirements for developing deep-learning algorithms that necessitate the joint development of hardware, datasets, and software.

1.3 Image Pre-processing:

Picture processing is a method of improving or extracting useful information from images by applying operations to them. It's a form of signal processing in which the input is an image and the output is that image or its characteristics/features. Image processing is one of today's fastest-evolving innovations. It is also a crucial research field in engineering and computer science. Image processing basically includes the following three steps:

- Importing the image using image acquisition software.
- Analyzing and manipulating the image.
- Output, which may be an altered image or a report based on image analysis.

2. Literature Review:

India is a country where still 70% of people still depend on agriculture as their main source of income, being such a high populous country there is always increasing demand for food supplies. Farmers face approx. 30% losses every year due to crops being affected by some diseases or due to some natural calamity.[3] If some plants do get affected sending them to the laboratory for results is a very time taking and risk-taking job as sometimes plants do get affected due to taking healing steps late. This problem can be solved using machine learning and deep learning and using such technology can help the farmers to detect the disease in a quicker way. In this study, we used the plant village dataset to train the deep learning algorithm[4]. To prevent this situation we need better and perfect guidance on which fertilizers to use, to make the correct identification of diseases, and the ability to distinguish between two or more similar types of diseases in visuals.

This is where a deep learning network comes in handy. Deep Learning helps us to distinguish between the objects that help to identify if a plant has a disease Convolutional Neural Network(CNN or Conv Nets) Deep Learning Model is best for such a scenario.

It is well known for its widely used applications of image and video recognition and also in recommender systems and Natural Language Processing(NLP). However, convolutional is more efficient because it reduces the number of parameters which makes it different from other deep learning models.[8]

Various techniques of image processing and pattern recognition have been developed for the detection of diseases occurring on plant leaves, stem, lesion, etc. By the researchers. The sooner disease appears on the leaf it should be taken to avoid loss. Hence a fast, accurate and less expensive system should be developed. The researchers adopted various methods for the detection and identification of diseases accurately. One such system uses a thresholding and backpropagation network. Input is a leaf image on which thresholding is performed to mask green pixels. Using k-means clustering segmented disease portion is obtained. Then CNN is used for classification.

1. Off-device image pre-processing using potato plant diseases identified Early blight and Blige using Leaf vein detection and Blob detection algorithm.

2. On-device image pre-processing on sugar beet diseases found Cerospora using Naïve Bayer classifier..

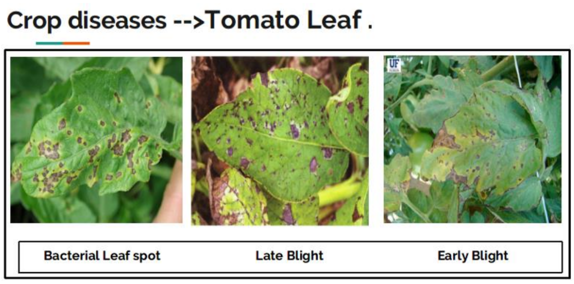
Authors	Approaches	Plant name	Diseases/Harvesting identified	Features Extracted	Classification Algorithm	Accuracy
Tasneem	Off-device images pre-processing	Potato	Early Blight and late Bling	Colour,shape	Leaf vein Detection and Blob detection algorithm	94.1%
`B.Klatten	On-device	Sugar	Cercospora	LBP	Naive Bayer	97%

	Image pre-processing	beet	beticola,Ramularia,Phoma Betae		Classifier	
Shovon Paulinus Rozario	On-device Image pre-processing	Paddy	Bacteria leaf Blight,Brown Spot Leaf, Leaf Scald	Blobs,Area and Colour	Euclidean distance of input and extracted images	Not given
Shitala Prasad	On-device Image pre-processing	Crop	Powdery Mildew,Downy Mildew,Late,Blight	Gabor Wavelet	SVM with RBF	98.96%
Shitala Prasad	On-device Image pre-processing	Plant	Leaf spots	K-means Segmentation	Weighted K-nearest	93%
Rahat Yasir	On-device Image pre-processing	Crop	Brown leaf spot,Bacteria leaf blight, Brown spot ufra and rice Blast	Colour	Histogram algorithm	85%
Alham F	On-device Image pre-processing	Palm oil	Hawar leaf,Anthracnose and Pestalotiopsis,Palmarum	Median of RGB,Quartile 1 of RGB,Standard deviation of RGB, Shape	Neural Network Classification	87.75%
Monika Bhatagar	On-device Image pre-processing	Tomato	Harvesting	Not given	Clustering	Not given

3. Methods and Dataset:

3.1 Dataset Description:

We examine 87k images of plant leaves that have 38 different class labels assigned to them. Each class label represents a crop-disease pair, and we attempt to predict the crop-disease pair based solely on the image of the plant leaf. Figure 1 depicts one illustration from each crop-disease pair in the PlantVillage dataset. We resize the images to 256 256 pixels in all of the approaches mentioned in this paper, and we perform model optimization and predictions on these downscaled images. The total dataset is divided into an 80/20 ratio of training and validation set preserving the directory structure. A new directory containing 33 test images is created later for prediction purposes. It contains 14 types of plants and 26 different types of diseases.
Example:



3.2 Measurement of Performance:

We run all of our experiments through a wide range of train-test set splits, namely 80–20, to get a sense of how our approaches can work on new unseen data and keep track of whether any of our approaches are overfitting (80 percent of the whole dataset used for training, and 20 percent for evaluation dataset).

3.3 Convolutional Neural Network:

Yann LeCun's creation of CNN in 1994 is what propelled the field of applied science and deep learning back to its former glory. Since then, we have come a long way in this area. The first neural network, called LeNet5, had a terrible validation accuracy of 42 percent. Almost all of the world's largest technology companies now depend on CNN for more effective efficiency. The use of CNN in detecting diseases in mulberry leaves is part of the definition. Before delving into the principle of "functionality and coping with CNN," we must first understand how the human brain identifies an entity despite its varying attributes.[5]

1.) There should be no missing values in our dataset.
2.) The dataset must distinctly be divided into training and testing sets, either the training or the testing set should‟t contain any irrelevant data out of our model domain just in case of an image dataset all the pictures must be of the identical size, one uneven distribution of image size in our dataset can decrease the efficiency of our neural network.
3.) The pictures should be converted into black and white format before feeding it into the convolution layer because reading images in RGB would involve a 3-D numPy matrix which might reduce the execution time of our model by a considerable amount.
4.) Any images that are severely distorted or blurred should be removed from the database before being fed into the neural network. Now that we've mastered the data preprocessing laws, we can plunge straight into the operation of the convolutional neural network.

A. Convolutional Layer:

The pattern is defined by scanning the entire image and preparing it in this layer as a 3x3 matrix. The decorated function of the image is referred to by the matrix kernel. Each value in the kernel is represented by a weight vector.

Here's how the structure of the convolution neural network looks so far:

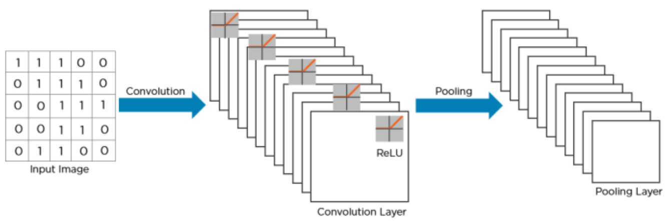


Figure 1- Convolutional Layer

B. Pooling Layer:

Pooling is a down-sampling operation that reduces the dimensionality of the feature map. The rectified feature map now goes through a pooling layer to generate a pooled feature map.

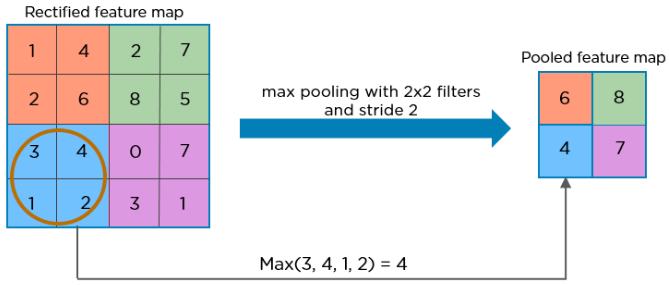


Figure 2- Pooling Layer

C. Activation Layer:

It is that part of the conversational neural networks where the values are normalized, fitting them within a certain range. The determination used is ReLU which allows only positive values and then rejects negative values. It is a function of low computational cost. [9]

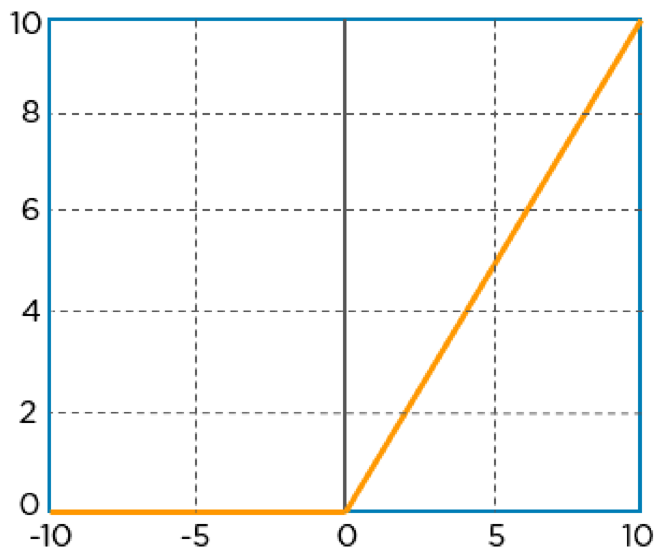


Figure 3 - Activation Layer

D. Fully Joined Layer:

The features are compared to the test image's features, and the same features are applied with the defined mark. Labels are usually encoded as numbers for numerical convenience; they will be translated to their respective strings later.

Artificial intelligence has made significant progress in bridging the difference between human and computer capabilities. Researchers and enthusiasts alike work on a number of facets of the world in order to produce amazing items. The field of computer vision is one of these. The agenda for this field is to permit machines to work out the world as humans see it, to perceive it in a uniform way, and even to use knowledge for a mess of tasks like image and video recognition, image analysis and classification, media recreation. recommendation systems, tongue processing, etc. Advances in deep learning computer vision are built and refined over time, primarily through a specific algorithm, a convolutional neural network[9][10].

3.3.4 System Architecture:

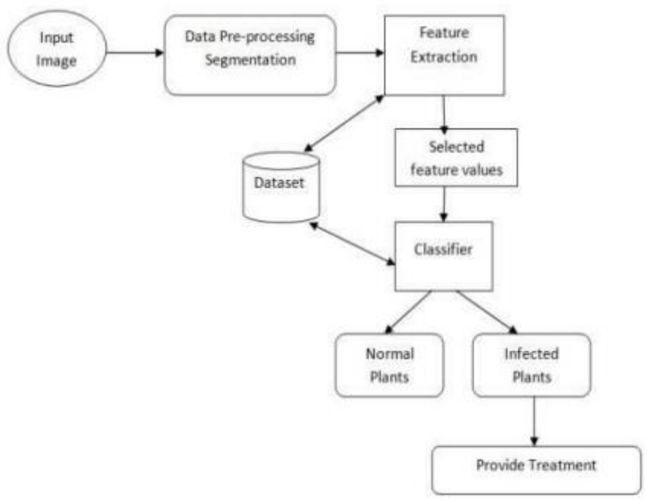
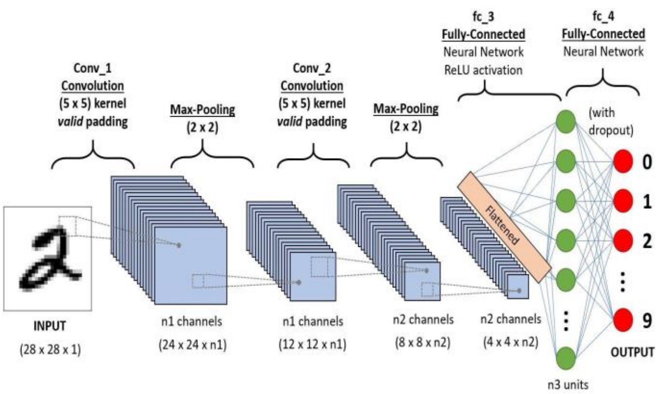


Figure 5- System Architecture

In our study, we have used the Plant Village dataset, which was trained using convolutional neural networks to predict the diseases of the plants. The images were then preprocessed and cropped. Then the images were trained on the deep learning algorithm to detect the diseases of the plants.

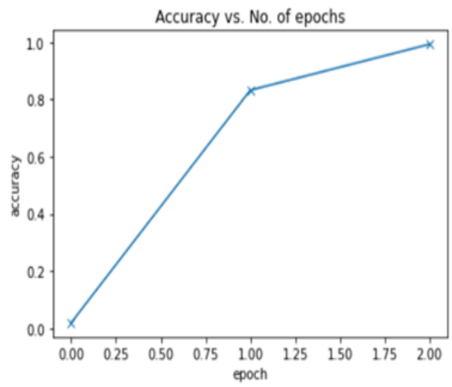


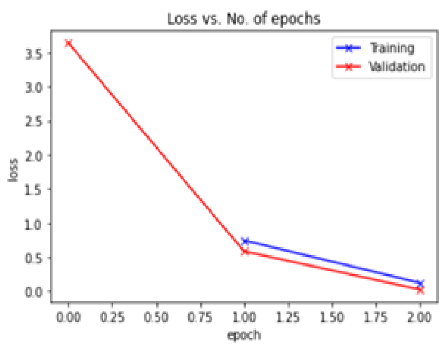
3.3.5 Transfer Learning:

Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task. It is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision and natural language processing tasks given the vast compute and time resources required to develop neural network models on these problems and from the huge jumps in a skill that they provide on related problems. [7]

4. Results:

At the outset, we note that on a dataset with 38 class labels, random guessing will only achieve an overall accuracy of 2.63% on average. Across all our experimental configurations, which include three visual representations of the image data, the overall accuracy we obtained on the PlantVillage dataset varied from 85% to 99.18%(using resnet architecture) see figure 1, hence showing a strong promise of the deep learning approach for similar prediction problems and loss of 0.0009.





To fix the problem of overfitting, we vary the test set to train set ratio and find that even when training on only 20% of the data and testing the trained model on the remaining 80% of the data, the model achieves an overall accuracy of 99.18% in the case of ResNet9 architecture. As predicted, the performance drop is not as severe as we would expect if the model was indeed over-fitting.

5. Conclusion

For several years, plant diseases have been a major source of concern in agriculture. Precision agriculture has allowed early disease detection and loss minimization through optimal decisions based on DL results. Recent advancements in deep learning (DL) provide solutions with highly accurate performance, and available hardware allows for quick processing. However, the decision-making process could be improved. Currently, usable models struggle to achieve high results when evaluated under real-world conditions. Motivated by this, and based on the authors' previous work, a novel method for plant disease detection was suggested in order to address significant functional limitations. This paper presented a new dataset containing photographs of leaves in natural settings, at various angles, and under various weather conditions, labeled for classification and detection tasks. Finally, the PlantDiseaseNet, a novel two-stage architecture for plant disease detection, was suggested. The trained model achieved an accuracy of 99.18 percent on the PlantDisease dataset and proved to be competitive in situations with complex surroundings due to its architectural design. The use of other information sources, such as location, temperature, and plant age, could theoretically improve accuracy. Future research should concentrate on detecting diseases in different parts of the plant and at different stages of the disease. The developed model could be used as part of a decision support framework, providing optimal decision-making conditions.

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