

# Next-Gen Agriculture: Deep Learning Algorithms for Real-Time Plant Disease Detection via IoT

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## Abstract

*In addition to providing high-quality food, the agriculture industry plays a critical role in supporting expanding people and economies. Plant diseases can have a detrimental effect on biodiversity and result in significant losses in food production. Automated methods for early and precise identification of plant diseases can reduce financial losses and enhance the quality of food produced. Deep learning has significantly improved object detection and picture classification accuracy in recent years. Thus, for effective plant disease identification, we used pre-trained convolutional neural network (CNN) models in this paper. An important aspect of the Indian economy is smart farming. However, structural changes to India's agriculture are already occurring, creating a catastrophe. Encouraging farmers to persist in crop production and turning agriculture into a viable enterprise are the only ways to address this dilemma. Our suggested methodology focuses on cultivation by employing machine learning to identify crop illnesses based on historical data and forecasting suitable crops based on climatic conditions.*

**Keywords:** CNN, Dataset, Kaggle, API, deep learning, agriculture.

## INTRODUCTION

Lack of food and water is becoming a major problem as a result of the unregulated global population expansion. A technical analysis released in [1, 2] predicted that by 2050, there will be 9.15 billion people on the planet. This tendency increases food production to support the growing global population, but it also reduces the amount of arable farmland and the number of farmers as fewer people opt to pursue careers in agriculture. For example, a winery in Virginia looked to hire foreign workers to harvest grapes because it couldn't find any Americans who would be interested in the job. The bulk of the fresh water on Earth is consumed by agriculture, even though it provides the food that is needed. The

agricultural sector uses one-third of Europe's water supplies, which affects the quantity and quality of open water that is accessible for other uses [3]. Mexico uses 75.72% of its water for agriculture [4]. For example, making a loaf of bread requires around 240 gallons of water, and making a pound of cheese requires about 382 gallons. Therefore, to prepare a simple cheese sandwich, 56 liters of water are required [5]. About 70% of India's population is dependent on agriculture, which is the country's main industry. Farmers can choose from a broad variety of crops and pesticides that are best for different types of plants. Plant diseases have the potential to significantly lower agricultural product quality and quantity. Agriculture is a vital component of human existence since it both maintains and alters the cycle of the food chain.

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Global population is expected to reach 9.1 billion people by 2050, according to FAO predictions made in 2017.”“ Farmers are searching for creative ways to grow a lot more grain in order to meet the world’s food needs [6].

Previously, there was a higher chance of not reaching food requirements due to human mistake and climate change. Natural disasters reduced the amount of agricultural products produced annually. The loss in agricultural production can also be attributed to other reasons, such as incorrect use of fertilizers and pesticides. Agricultural profitability is lowered by the considerable human participation and conventional methods used in each stage of crop growth. Since the dawn of time, human populations have demanded food production. Humanity has been impacted by food scarcity since the beginning of time.

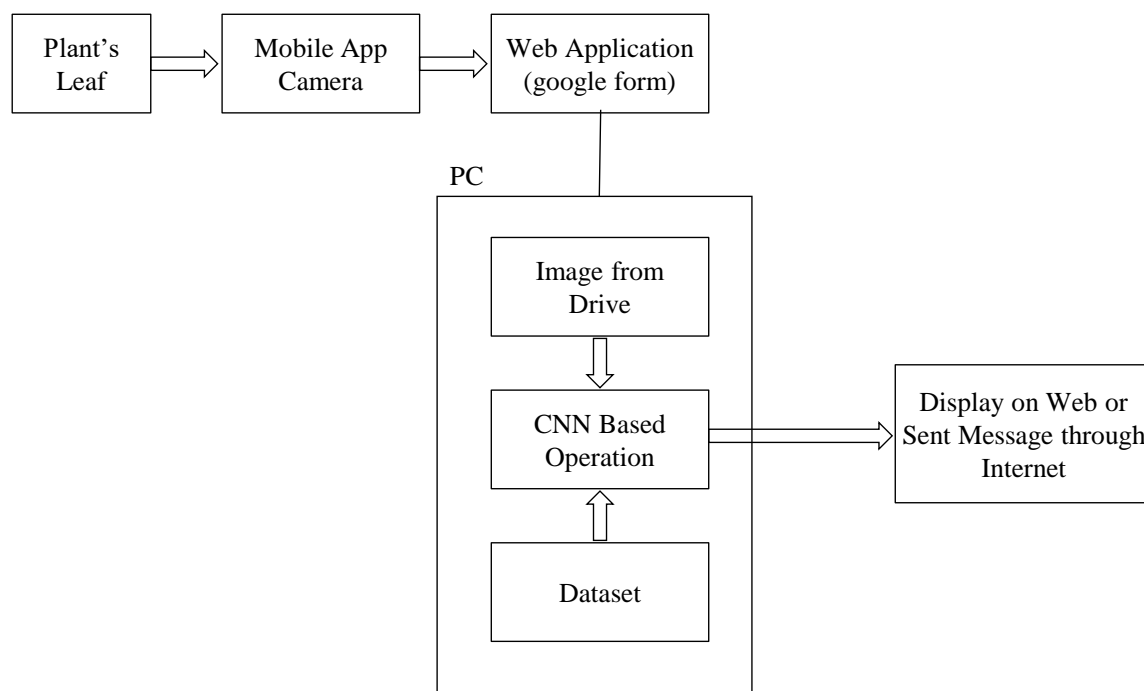
Due to limited water and land resources, human needs will increase during the next ten years. Food production is in great demand due to the scarcity of land and water [7].

Plant visual patterns are observed in order to understand plant diseases. Keeping an eye on plant ailments and health is essential to farming crops successfully. Plant disease specialists used to manually monitor and analyze the illnesses on plants. This took a long time to process and a lot of work. By using a machine learning model that has been trained on photos, our system can distinguish between healthy and unhealthy leaves and produces reliable findings [8–15].

## METHODOLOGY

On an operating system, machine learning models that have been trained and evaluated to identify agricultural leaf diseases are kept. By uploading a photograph to a locally hosted website, you can determine whether or not a leaf is infected. The operating device functions as the system’s central processing unit. The machine learning (ML) model, trained to identify plant leaf diseases, is stored there. A personal computer (PC) or a comparable device with adequate processing capability can serve as the operating device. It executes the applications required to manage data processing and ML model inference, such as an IDE for Python.

*Block Diagram:* Block Diagram of proposed system is shown in Figure 1.



**Figure 1.** Block Diagram of proposed system.

### LITERATURE REVIEW

A review of the academic literature on a particular subject or research question is called a literature review. To place the work in context of current knowledge, it is frequently written as a component of a thesis, dissertation, or research paper. Data has been gathered via our survey. A well-written literature review provides a comprehensive picture of the state of knowledge on a subject by critically analyzing, synthesizing, and summarizing sources as well as critically evaluating them.

**Table ?**

Title	Author	Methodology
Deep learning for image-based plant disease detection	Mohanty et al. [4]	Convolutional neural networks (CNNs)
Deep learning models for plant disease detection and diagnosis	Ferentinos [16]	CNNs, Transfer Learning
Deep learning for plant disease detection and saliency map visualization	Spasojevic et al. [17]	CNNs, Attention Mechanism, Explainability

### CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional Neural Networks (CNNs) are deep learning algorithms that are mainly employed in computer vision and image recognition applications. It is made up of multiple connected layers that work together to extract useful characteristics from input photos. This is a succinct description of how CNNs operate:

1. *Convolutional layer:* A collection of learnable filters, sometimes referred to as kernels or feature detectors, convolve the input image. To create a feature map, each filter performs element-wise multiplication and aggregation while scanning the image in small sections. Spatial hierarchies and local patterns are captured by convolutional layers.
2. *Activation function:* Next, to provide non-linearity and enable the network to understand intricate feature correlations, the feature map is run through a non-linear activation function (such as ReLU).
3. *Pooling layer:* A pooling layer is used to lower spatial dimensionality and increase the learned features' resistance to change. Two popular pooling techniques are average pooling, which determines the average value, and max pooling, which chooses the maximum value in each zone. Pooling facilitates translation invariance and lowers computing cost.
4. *Fully connected layer:* A conventional neural network design, usually consisting of fully connected layers, is coupled to the flattened output of the convolutional and pooling layers. These layers use the retrieved characteristics to learn high-level representations and forecast the future as shown in Figure 2.
5. *Output layer:* An activation function appropriate for the given task, like sigmoid for binary classification or softmax for multi-class classification, comes after the last completely connected layer. It produces the class predictions or output probabilities for the network.
6. *Training:* In order to minimize a loss function, CNNs are trained using optimization techniques such stochastic gradient descent and backpropagation. By utilizing relevant measures, such as cross-entropy, to compare the true labels with the anticipated output, the loss is calculated.
7. *Optimization:* To reduce the loss as much as possible during training, the network's weights and biases are modified iteratively. To increase computing efficiency, batches of input photos are usually processed using this method.
8. *Evaluation and prediction:* After been trained, a CNN can be applied to new, untrained pictures to make inferences. Applying the learnt filters and calculating predictions using the learned representations, the forward pass through the network makes its way.

### RESULTS AND ANALYSIS

The output produced by the convolutional neural network (CNN) model when examining an input leaf picture for plant disease diagnosis is shown in the figure named "Prediction of image (analysis)".

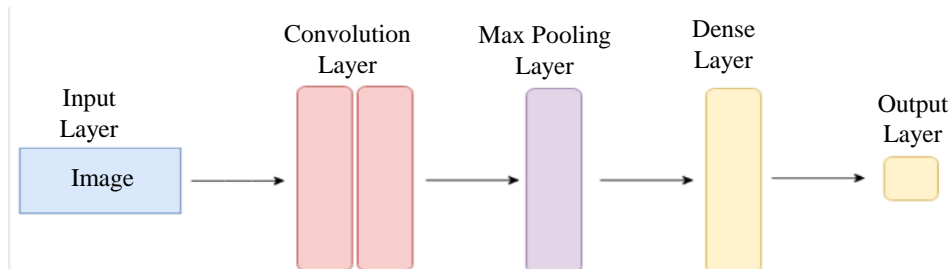
The leaf image, which was probably fed into the trained CNN model, is displayed in the main area of the graphic. Textual data indicating the model's analysis or prediction for that particular input image surrounds the leaf image.

Even though the writing is not clearly visible in this low-resolution image, we may deduce that it contains information about how the model evaluated the leaf's condition. Generally, the output of these plant disease detection systems would specify whether the input leaf is considered healthy or diseased. Furthermore, the analysis could incorporate the likelihood score or confidence level linked to the prediction, together with details regarding the disease type identified, if relevant.

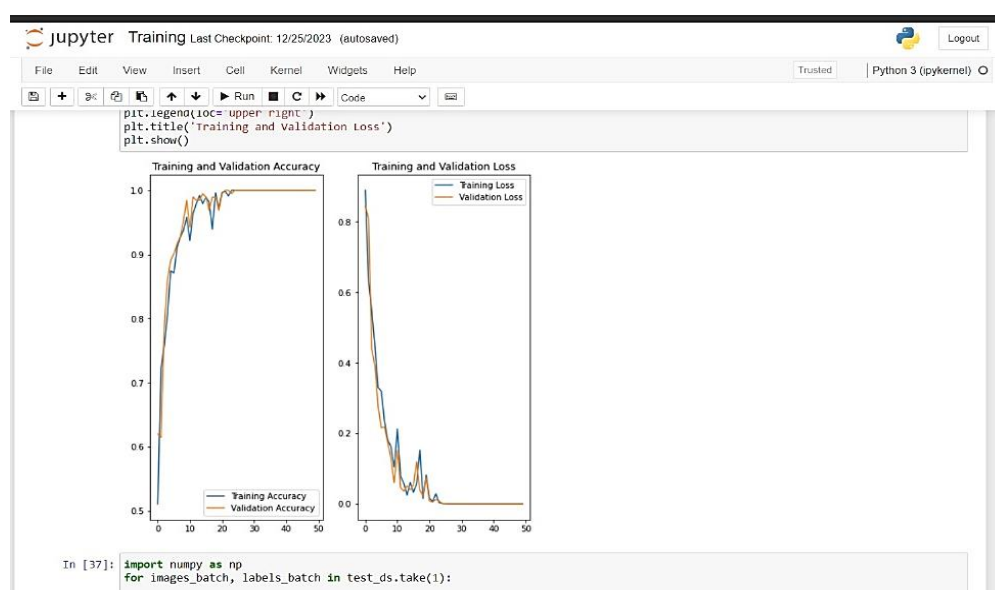
This graphic illustration shows how the CNN model is used in practice by processing a leaf image and producing a diagnostic result that indicates whether or not illnesses are present in the plant. The developed system's primary analysis component is the textual information around the leaf image( as shown in Figure 3), which encodes the model's prediction. Prediction of image (analysis) is shown in Figure 4 and results of image is shown in Figure 5.

## APPLICATIONS

- i. *Agriculture*: By focusing on disease-affected areas, farmers may reduce their usage of pesticides and fertilizers while also saving money and the environment.
- ii. *Plant Research*: Deep learning speeds up plant pathology research, allowing researchers to better understand illnesses, create crop types that are resistant to them, and increase total agricultural yield.
- iii. *Global Food Security*: Deep learning technology significantly contributes to providing food security for the world's expanding population by reducing crop losses brought on by illnesses.



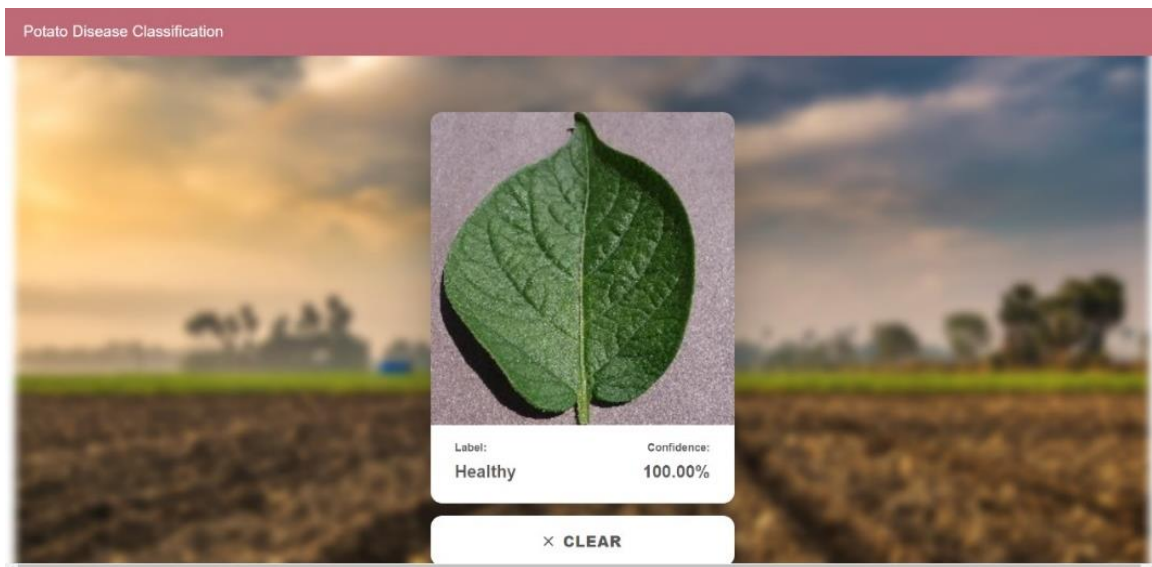
**Figure 2.** CNN Layers.



**Figure 4.** Prediction of image (analysis).



**Figure 3.** Some pictures of leaves.



**Figure 5.** Result of Image.

**FUTURE SCOPE**

- i. *Improved Accuracy:* With continued research and development, deep learning models for plant disease detection may become even more dependable and accurate, lowering the number of incorrect diagnoses and increasing crop production.
- ii. *Real-time Monitoring:* By integrating IoT devices, it is possible to monitor plant health data in real-time, including temperature, humidity, and soil moisture. This facilitates early disease identification and prompt intervention.
- iii. *Integration with Agriculture Machinery:* By integrating agricultural machinery—such as robotic systems or drones—the monitoring and treatment process can be made even more efficient, maximizing resource use and reducing the need for human intervention.

**CONCLUSION**

Plant disease detection is a common use of CNN algorithms. The issues with conventional object identification and classification techniques have been resolved. We provided a thorough analysis of

CNN-based research on plant leaf disease detection in crops conducted throughout the last five years in this paper. A total of 100 publications were reviewed, covering topics such as detection techniques, model performance assessment, popular CNN framework comparison, in-depth descriptions of CNN applications in agricultural fields, dataset preparation, issues and solutions pertaining to the detection of plant leaf diseases, and publicly available datasets in the relevant field. We analyzed research articles that were closely linked in order to provide a comparative study of different CNN models.

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