International Journal of Basic and Applied Sciences, 14 (4) (2025) 55-66

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/b9c87e95
Research paper

Cascaded CNN For Early Detection of Plant Diseases Machine Vision Techniques in Smart Agriculture

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Received: June 19, 2025, Accepted: July 30, 2025, Published: August 4, 2025

Abstract

Plant disease detection is important because plants absorb the greenhouse gases emitted by industries and vehicles and liberate oxygen, to extend human life in the Universe. The biodiversity chain is fully reliant on plant growth and mainly purifies the air and makes it suitable for respiration. Various diseases like Bacterial Spot (BS), Early Blight (EB), Late Blight, Mold (LBM), Leaf Spot (LS), Spider Mites (SM), Target Spot (TS), and Yellow Leaf Curl (YLC) attack the plants, causing retardation in plant growth, thereby offering stress to the plants. Plant stress reduces crop productivity and creates a deadly impact on the economy. Several studies have exhibited that the quality of agricultural products is seriously affected due to plant stress. Plants are stressed due to many reasons like extended use of synthetic fertilizers-ers, soil nutrients, plant diseases, and the various physiological parameters like atmospheric temperature, sunlight, soil pH, and soil moisture content, which may vary seasonally. The benchmark images of the leaves under normal conditions are gathered, and pre-processing is per-formed. Further, the feature extraction is done by various types of Convolutional Neural Network (CNN) models like Faster Region-based CNN (FR-CNN), R-CNN, Cascaded CNN, and compared with the standardized CNN model. An optimal solution is offered using Artificial Intelligence (AI) for early-stage detection of chlorophyll content and as well as plant disease prediction. The important advantage of AI AI-based detection approach is to identify the leaf area turning yellow or brown at the start with optimal accuracy.

Keywords: *Plant Disease Detection; Deep Learning Neural Networks; Artificial Intelligence; Plant Stress; Smart Agriculture; Cascaded Convolutional Neural Networks.*

1. Introduction

The advancements in AI have facilitated its usage in plant studies, predominantly in the domain of chlorophyll, which is promoting modernization that guarantees to transform the comprehension interaction in the agriculture field. Optimization of crop yield helps to combat the ill effects of climate change. AI-enabled technology enhance the capacity to harness the potential of plants extraordinarily. This work projects the implementation of AI in transforming the conventional approach of chlorophyll measurement, a green coloured pigment that is responsible for photosynthesis. AI and image processing are mainly used in rapid technologies to modify the hyperspectral images related to agronomy. The degree of realism is high for plant disease identification from the green colour of the leaves using an automatic detection system. In the modern era, there are many software packages developed for image processing applications, and these applications are accessible and subjected to real-time modifications [1].

Chlorophyll is a green coloured pigment which is the lifeblood of plants, facilitating photosynthesis by which the plants manufacture their food in the presence of sunlight, thus converting light energy into chemical energy. During photosynthesis, this green colored pigment plays a critical role in oxygen production and carbon dioxide absorption. Expansion in AI is providing a path for image-based analysis to predict and estimate the chlorophyll content with high precision, leading to significant agricultural and environmental benefits [2].

Leaf morphology involves the measurement and investigation of evident characteristics that contribute to plant growth, colour, and structure of the leaves, depending on the chlorophyll content. If AI methods are used, the prediction of chlorophyll content is a simple task compared to the conventional methods that are tedious and laborious, consuming much time. AI technology serves as a game changer that incorporates ML algorithms with the capacity to process large data sets obtained from leaf images, spectral data, and environmental sensors to spot out the restrained morphological characteristics with optimal accuracy [3].

1.1. Major threats in agriculture

Due to an increase in the world's population, the scarcity of food is also increasing proportionally. Lack of irrigation lands and demand for water supply have made agriculture a challenging task for farmers. Smart agriculture incorporates modernization in agronomy to amplify the crop yield [4]. The major risks for the plants are classified and illustrated in Figure 1.

- Choice of the proper seeds: Choice of appropriate seeds to be sown in the cultivation lands is of great importance because the growth of the crops in that field depends on factors like soil wetness, soil nutrients, and soil pH, which contribute to the growth of the crops, giving high yield [5].
- Methods of Irrigation: Irrigating the cultivation lands is the secret behind high crop yield. Based on the nature of the crops to be grown, farmers can select any one type of irrigation system that is in conventional use. They include sprinkler, drip, subsurface, surface, and center pivot irrigation systems. Use of modern irrigation methods involves the usage of temperature, moisture, pH sensors, which are networked together using Internet of Things (IoT) and AI to offer guidance in maintaining the required water level and nutrients near the roots to increase the agricultural produce [6].
- Prognostic Analysis: Prediction helps to make decisions on seed sowing, monitoring the plant stress, soil fertilizer management, Pest treatment, water supply for irrigation, pH level, and sunlight intensity. The decision-making process is carried out by the expert system [7].
- Estimation of Soil Nutrients: Inconsistency in the soil composition needs to be identified by soil analysis to supply the appropriate nutrients to the soil in estimated quantities [8].
- Weather Forecast: Climatic conditions play an essential part in enhancing the growth of the plant. Depending on the climatic conditions, crops are classified as Kharif crops grown during the rainy season (absorb large quantities of water from soil), Rabi crops cultivated in the winter season, and Zaid crops grown in the summer season (requires very less water or even no water, suitable to be grown in dry lands) [9].
- Removal of Invasive plants: This includes effective removal of weeds, which are unwanted plants grown amid the useful crops, using Image Processing (PI) and AI methods. Enhanced weed growth can affect the growth of the useful crops and decrease productivity. Weeds consume water, fertilizers, and pesticides that are supplied to useful crops, thereby decreasing the yield of the required crops and leading to excessive usage of all the above, which increases the maintenance cost of the fields [10].
- Sunlight, Water, and Minerals Supply to plants: Plants require water, sunlight, and minerals for photosynthesis, a process by which plants prepare their food. Machine Learning (ML) algorithms can predict the required amount of water; sunlight and minerals are needed for the plant's growth [10].

1.2. Ecological conditions

Ecology plays an important role in creating an environment for enhanced plant's growth. Due to variations in environmental conditions, the parameters like rainfall, humidity, sunlight intensity, and pH value vary, which causes diseases in the crops. Various organisms like bacteria, fungi, viruses, etc., serve as disease-causing agents in plants. These pathogens multiply when the environmental parameters are favourable for their growth, thereby spreading the disease to the entire plant, affecting the productivity [11].

Rainfall and Humidity: During rainy seasons, the moisture content in the soil will be very high which is favourable for the growth of fungus causing some common diseases like grey mold, early blight, yellowing of the leaves, leaf spots, Molds and Blights, are a few to be mentioned, on discussing about rainfall and humidity [12].

Soil Fertility and pH level: An increased or decreased level of soil pH affects the soil fertility. It increases or decreases the nutrients in the soil, making the plants highly prone to diseases. Alkaline and acidic soil can cause scab disease in potato plants and bacterial wilt, respectively. The other diseases include mottling, chlorosis, necrosis, and root damage [13].

Temperature, wind, and Sunlight Intensity: The temperature is one such parameter that facilitates the growth of the microorganisms in plants. Fungal diseases occur in plants during the rainy season due to excess water content in soil, low atmospheric temperatures, and decreased sunlight intensity. If the atmospheric conditions are dry, very hot, and with high atmospheric temperatures, plant diseases like spores are formed [14].

1.3. Micro-organisms causing plant diseases

The three major microorganisms responsible for causing plant diseases are viruses, fungi, and bacteria [15]. The two sides of the coin responsible for plant diseases are the microorganisms and environmental factors.

Viral diseases in plants: It is a subdivision of the microorganism category that causes infections and spreads only inside the living cells. Plants that are affected by leaves turn yellow and have stunted growth. Cucumber plants are the best example of being affected by the mosaic virus, and it spreads from one plant to another plant by pollination. To avoid the spreading of viral diseases in plants, one can just truncate the part of the plant that is virus-affected [16].

Fungal diseases in plants: Ascomycetes and Basidiomycetes are the two main types of fungal diseases that occur in plants. Fungicides are used to fight against fungal diseases. For example, fungus-like Phymatotrichopsis omnivorum is responsible for cotton root rot. Plants, when affected by fungal diseases, turn yellow and may wither off, droop, and dry suddenly [17].

Bacterial diseases in plants: Bacteria are unicellular microorganisms. Wilt, spots, and scabs are the diseases caused by bacteria. Water absorption in plants is blocked by the infections caused due to bacteria. Some bacteria responsible for plant diseases are Erwinia amylovora, Pseudomonas syringae, and Ralstonia solanacearum [18].

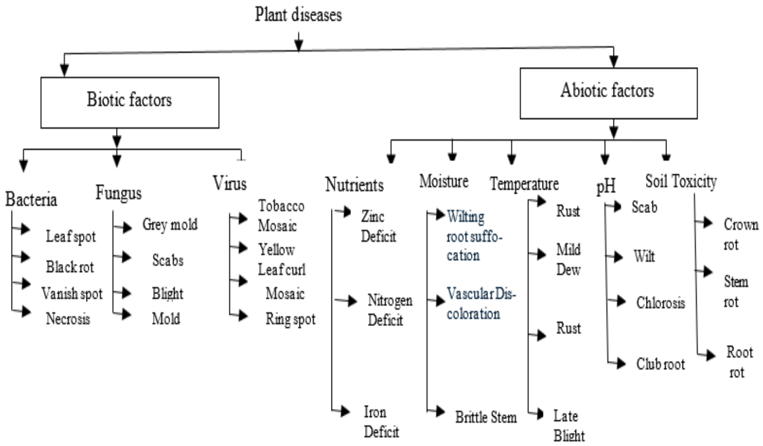


Fig. 1: Tree Diagram for Factors Inducing Diseases in Plants.

1.4. Machine learning (ML) and image processing (IP) in the prediction of plant diseases

It is a sub-domain of AI that makes use of computerized programs for learning, analyzing, recognizing, and decision-making using the data patterns available from the plants. ML algorithms require a large amount of data, offer improved performance over time, and perform tasks without unambiguous instructions. They include supervised (Classification and regression), unsupervised (Clustering and Dimensional reduction), semi-supervised (self-training, co-training, Generative Adversarial Networks-GAN), self-supervised (cropping, rotating, or noise addition), and reinforced learning (model-based and model-free) methods [19]. Pictorial representation of the ML methods is given in Figure 2.

Image processing is a technique that uses algorithms for the manipulation of digital images. The various sub-domains of IP include (Figure 3) Image transformation, noise filtering, image enhancement, image analysis, and image compression [20].

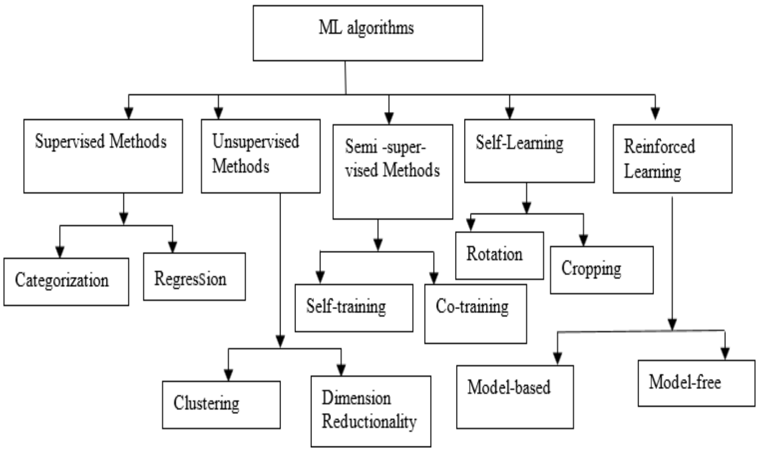


Fig. 2: Categorization of ML Algorithms Used in Plant Disease Detection.

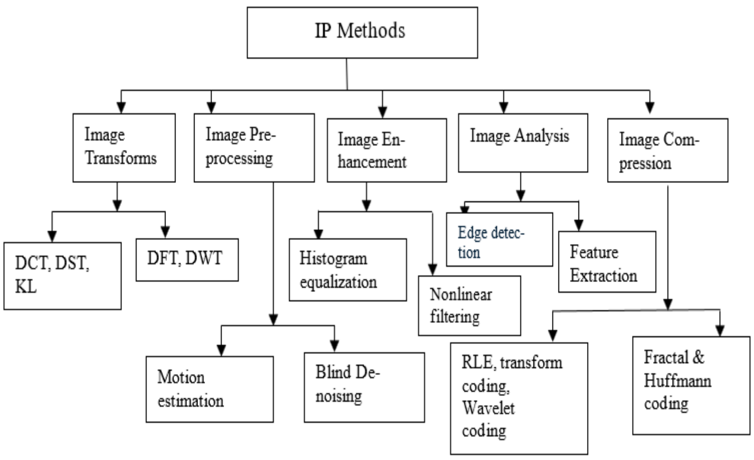


Fig. 3: Classification of IP Methods for Plant Disease Identification.

1.5. Objective of the work

The specific goals that can be achieved from this study are listed below:

- Hybrid AI-ML System Design: This is to design an AI-ML-based system that integrates leaf disease detection for detecting various types of leaf diseases occurring in Bell Pepper, tomato, and potato plants.
- Categorization of Plant Diseases: To classify whether the plant diseases are at the early stage or late stage through a deep learning categorization algorithm
- Leaf Diseased Area Estimation: To estimate the size and extent of the leaf disease, it is considered vital for both staging and pesticide treatment purposes.
- Minus Disease detection Errors: To prevent false positives and false negatives, as well as to enhance Disease detection sensitivity and to reduce spurious agricultural interventions.
- Ensure real-time analysis capability: To make the system provide speedy and reliable results, integration in the agricultural fields.

2. Laboratory scale or existing/traditional method of chlorophyll measurement

The instrument used for measuring the chlorophyll content in the leaves is called a Chlorophyll meter or SPAD meter. This meter indicates the chlorophyll content in the plants, which helps in the enhancement of crop productivity and yield. The chlorophyll content in the plants indicates the condition of the plant and determines the need for additional usage of fertilizer. The nutrient levels can be optimized and healthy crops can be grown by detecting the chlorophyll content. The principle behind the chlorophyll measurement is based on the absorbance phenomenon (optical density difference) in the red and near infrared regions or blue (ultraviolet) and red (infrared) regions [21]. The chlorophyll content is directly proportional to Nitrogen (N) content and other nutrients present in the plants. This device that is used for chlorophyll measurement is a compact, portable, light-weight, water-resistant, low power consumption device with data storage, capable of producing high precision readings from a small area of measurements. By measuring the chlorophyll content, the amount of nitrogen present in the plants can be determined. As a result, N-management and N-fertilizer supplements can be automated. By reducing the excessive supply of nitrogen through fertilizer, the excessive supply of fertilizers can be optimized and controlled [22]. The chlorophyll meter is shown in Figure 4(a) and (b).

Fig. 4: A): Procedure for Using the Chlorophyll Meter.

Fig. 4:B): Parts in the Chlorophyll Meter.

3. Literature survey

Rei Sonobe, etal.(2020) discussed the tea plants grown in the shady regions to increase their chlorophyll content, thereby influencing the quality of green tea. Tracking the chlorophyll level under low light conditions is important for supervising the tea plants and producing premium quality green tea. Remote sensing is used for chlorophyll estimation from hyperspectral imaging. The tea plants grown in shady areas lack chlorophyll content, which is studied from the data collected under relatively low-stress conditions with various hyper-spectral incidences generating radiative transfer models. For performance evaluation, ML algorithms like random forest, SVM, Deep Belief Nets (DBN), and Kernel-based Extreme Learning Machine (KELM) are implemented. Variation ranges from 1.7 to 8 on the test data set, suggesting that KELM is effective in tracing the chlorophyll changes for tea plants grown in shady areas [1].

Kowshik Kumar Saha et., (2024) [2] have discussed that climacteric fruits like Tomato (Solanum lycopersicum L.) show the colour change (from green to red), indicating the pattern of ripening. Normalized difference vegetation index (NDVI) is an index calculated from the optical spectrum for analyzing the ripening quality based on the strong correlation between the ripening quality and the level of chlorophyll. Light Detection and Ranging (LiDAR) captured the 3D gain in estimating the spatial values concerning the chlorophyll content in the tomato plants. The six stages of ripening for tomato are classified as green, pale yellow, deep yellow, pink, pale red, and dark red according to colour standards. A sensor system incorporated with two LiDAR units was used for measuring signal strength corresponding to various intensities. The overall accuracy is around 70 %.

A standard and intervallic crop health monitoring is necessary for cultivation. Chlorophyll is a vital component that denotes plant health. Betel vine stands in the second place of consumption next to coffee and tea. Hence, these cash crops are chosen for investigation. The experimentation was carried out in a well-grown betel vine crop field. The conventional way of leaf chlorophyll measurement is done, and it has its disadvantages. As a result, a rapid and specific chlorophyll measurement technique for leaves is required. Schemes incorporating image processing algorithms based on tri-color determination, Red (R), Green (G), and Blue (B) models, are projected here. Regression analysis is carried out by correlating the output of the RGB model with the chlorophyll meter reading. Thus, the researchers found that this method was fruitful in measuring the chlorophyll from the leaf colour using image processing techniques [3].

R. Kavitha Lakshmi et., (2021) [4] proposed the uses of sustainable agriculture. AI was deployed for the recognition and identification of plant diseases. Automated detection can make the task simpler in a short duration, though the disease symptoms on the surface of the leaves are directly visible. Recently, the automatic diagnosis of plant diseases has been done using neural network models with deep learning algorithms. The major challenge in implementation is over-fitting during the training process. Ensemble Convolutional Neural Network (ECNN) is used for the classification of plant leaf diseases, and its performance was compared with other types of deep learning models like VGG16, ResNet152, Inceptionv3, and DenseNet121. Three crop varieties with 18 distinct groupings were used from the plant village dataset. An accuracy of 98.96% was achieved as compared with the benchmark models.

Kishor Chandra Kandpal et., (2023) [5] have presented a method for examining and estimating of chlorophyll content present in the leaves on a laboratory scale as well as in the field. The re-evaluation consists of two parts, the destructive and non-destructive methods for the estimation of chlorophyll. Arnon’s spectrophotometry is found to be a famous and uncomplicated scheme for the evaluation of chlorophyll content present in leaves in the laboratory. Android applications and handy apparatus for chlorophyll measurement have facilitated the onsite measurement. Plant-specific algorithms were used in this application. Remote sensing images with hyperspectral use 40 plus indicators for the determination of the chlorophyll content. The authors of this paper have recommended performance indicators like tri-band hyper spectrum vegetative index, Chlorophyll green colour, Triangle Green colour Index, Wavelength Deviation Index, and Normalized Chlorophyll deviation for chlorophyll estimation in a variety of plants. Algorithms like Random Forest, SVM, and Artificial Neural Network regressions are used for chlorophyll determination.

Utkarsha N, et., (2020) [6] discuss that the characterization and monitoring of plant growth depend on the morphological composition. They have introduced a well-organized approach to categorize the healthy and unhealthy plants from the leaf surface using IP and ML algorithms. Loss of chlorophyll causes brown/ black spots on the leaf surface. SVM and CNN are compared in terms of the maximum accuracy achieved.

A huge amount of economic loss is added to the agricultural industry globally because of the plants being affected by various types of diseases. Currently, the challenges in this domain deal with the expansion of the consistency of the methods for the identification of plant diseases. Presently, the plant disease identification involves manual and visual assessment of the crops using disease indicators that are visible to the naked eye. Increased precision is achieved in plant disease detection by using hyperspectral imaging in designing Unmanned Aerial Vehicles (UAVs). UAVs are built with intelligent systems for precise and economical effective crop diseases. Lukas Wiku Kuswidiyanto et., (2022) classify the hyperspectral images of the plants and vegetation to monitor their health conditions using ML algorithms [7].

The selection of superior quality leafy vegetables relies on the agronomic characteristics of the plants, in which the green colour of leaves exhibits the morphological characteristics with a direct impact on the growth of such plants. Ziran Ye et., (2024) have suggested the method of leaf image analysis by morphological and structural feature extraction, in predicting the chlorophyll content of the lettuce plants cultivated inside a greenhouse. CNN is used for hyper-spectral image analysis of disease detection with an average RMSE of 2.018 [8].

Seyed Mohamad Javidan et., (2024) [9] pointed out that AI classifiers perform differently depending on the features extracted and used to classify them to identify the plant diseases that can drastically lessen the crop yield. Juan Ignacio Arribas et., (2011) 10 presented a leaf image classification system without human intervention in the sunflower crops using neural networks to allow the usage of selective pesticides. The system includes segmentation based on RGB color space, feature extraction/discrimination, and a Generalized Softmax Perceptron Neural Network (GSPNN) for classification. Posterior Probability Model (PPM) is used for the selection/categorization of leaves belonging to sunflower or non-sunflower plants. The upper limit of the Correct Classification Rate is 85% and the Receiver operating curve is 90%.

The ML-based computerized scheme forms a subdivision of pattern recognition algorithms that enable the identification of leaf diseases. In the year 1958, Rosenblatt analysed the cognitive, emotional, and social behavioural patterns of human beings and proposed a concept called Artificial Neural Networks (ANN) that mimicked the human brain in the Central Nervous System (CNS) [18]. Attributes are generated from the leaf surface of the infected cotton plant were extracted by Al Bashish et al [19] for implementing ANN for classification and recognition of the disease with an accuracy of 93%. Principal Component Analysis (PCA) was used for optimizing the extracted feature size by Wang et al. [20], [21], and used is as input to Back Propagation Neural Network (BPNN) for disease classification in grape and wheat plants. Recently, a literature survey states that Bacterial Foraging Optimization (BFO) was used for tuning the weights of BPNN and Radial Basis Function Neural Network (RBFNN) [22]. BPNN-BFO proved to be beneficial [23] for the successful classification of the plant diseases. The diseases that occur in mango tree leaves were detected at an early stage by Pham et al. [24] using the ANN model.

Friedman et al in 1975 used K-nearest neighbour for leaf disease classification. Liaghat et al. [25] used Support Vector Machines (SVM) for detecting the incurable fungal diseases in oil palm plants with an accuracy of 97%. Five different diseases that affect the leaves of the maize plantations were detected by Zhang et al. [26], and they obtained 91% accuracy using KNN. To improve the classification efficiency, the conventional KNN was combined with Fuzzy Logic (FL) [27], which resulted in an accuracy of 93.38% [28].

Maximum margin theory was introduced into SVM by Cortes and Vladimir [29, - 32], [38] to offer an optimal solution for twofold classification challenges for detecting plant diseases. Hyperspectral images that are dependent on the reflectance model of the spectrum are widely used for remote sensing-based plant disease classification systems. A slightly varied method called Multi-Birth SVM (MBSVM) was incorporated by Yang et al. [33], [40] for plant disease detection.

Pomegranate leaf diseases were detected by Bhange and Hingoliwala [34] using SVM with an accuracy of 92%. Neural Network Ensemble SVM (NNESVM) ([35 - 37]) is another new technique introduced in this field for the purpose of plant disease classification. ML and Deep Learning (DL) algorithms were incorporated by Wani et al. [38] for leaf disease identification, achieving an accuracy of 97.5%. Potato late blight was detected by Thomas et al. [39 - 41] from hyperspectral images using SVM for classification purposes.
Motivated by SVM, Jayadeva and Suresh [42] deployed the idea of Twin SVM (TWSVM), where a binary classifier detects the infected areas of the plants using two unparalleled hyperplanes. Fuzzy Twin Support Vector Machine (FTSVM) was deployed by researchers [43] to identify plant diseases from their respective leaf images. The Least Squares Twin Support Vector Machine (LSSVM) model was incorporated by Tomar and Agarwal [44] for identifying the disease-affected regions of the leaves to attain a noteworthy output.
Therefore, analysing the various modalities of computing vision techniques, automation of the agricultural processes has shown a way for the development and real-time implementation of smart agriculture [45, 46]. To have a quick glimpse of the entire survey, a crisp message about the research carried out by the researchers in the smart agriculture is depicted in Table 1.

Table 1: Benefits And Challenges of AI-Driven Chlorosis Detection Models Using Deep Learning

Author/Year[citation]	Methodology	Features	Challenges	Inference
Rei Sonobe, etal.,(2020)	random forest, SVM machine, deep belief nets, and KELM	Hyper-spectral indices under low-stress conditions	Chlorophyll increases for tea plants grown in shady areas	Hyper-spectral reflectance and KELM Deviation values range from 1.70 to 8.04
Kowshik Kumar Saha, et., (2024)de-Sasse.	Normalized difference vegetation index LiDAR	Geometric correction with curvature in tomato, and the highest intensity areas are eliminated	Six stages of ripening for tomato - classified as green, pale yellow, deep yellow, pink, pale red, and dark red	Overall accuracy is around 70 %.
Amar Kumar Dey., etal., (2016)	Regression analysis is carried out by correlating the output of the RGB model with the chlorophyll meter reading	RGB model of the betel vine leaves - histogram function	Chlorophyll content - directly proportional - nitrogen present - disadvantage of light intensity - digital camera	Mean brightness ratios were evaluated
R. Kavitha Lakshmi, et., (2021)	Ensemble Convolutional Neural Network	Membership probabilities	Over-fitting and increased processing time for training	Accuracy of 98.96%
Kishor Chandra Kandpal, et., (2023)	Arnon’s spectrophotometry	Random Forest, SVM, and Artificial Neural Network regressions	Reflectance-based vegetation indices and chlorophyll fluorescence imaging methods	Wavelength Difference Index and NDVI were found to be appropriate for performance evaluation
Utkarsha N, etal., (2020),	SVM and CNN models for feature extraction and classification	Grey Level Co-occurrence Matrix (GLCM)	Diseased or not diseased	Overall accuracy is found as 97.71% using CNN and 80% accuracy – SVM
Kuswidiyanto, etal., (2022)	Hyperspectral images of the plants and vegetation are used to monitor their health conditions using ML algorithms	Hyperspectral features - Using full spectrum, Band reduction-PCA, Vegetation indices	Early disease detection and limited datasets for Pine vegetation	Accuracy of 97.22%.
Ziran Ye, etal., (2024)	CNN is used for hyper-spectral image analysis of disease detection	Morphological and structural feature extraction	Measurement of leaf senescence, plant height, and growth period is challenging	RMSE of 2.018
Seyed Mohamad Javidan ., etal., (2024)	Deep learning Model	color, texture, and shape	Lack of an expert system-occlusion issue	Accuracy 60% to 90%
Juan Ignacio Arribas , etal., (2011).,	Posterior Probability Model Selection	perimeter, area, major ellipse axis, minor ellipse axis, and logarithm of the height to width ratio	Image bank -717 - positive classification -1434total samples - training: 50% positive (sunflower) and 50% negative (non-sunflower or weeds)	The Correct Classification Rate is 85% and the Receiver Operating Curve is 90%

Overall, agriculture forms the basis for recent advancements and development of human beings in society [46, 47] for decision-making so as to extend the survival of human lives [48]. As an up-and-coming skill set, computerized vision machine technology combined with AI for a computing machine vision solution is an essential condition for civilizing the methods in agriculture, to improve its efficiency and has a broader prediction about the future of agriculture and its associated relevance in research [49, 50]. Computerized vision machine technology will be improved using AI and IP methods for automation of the agricultural processes and robotics in farming.

4. Cascaded CNN architecture

To detect the diseased areas of the leaves in multi-scales, it is initially required to change the input image size into diversified scales for building an image pyramid. This serves as the input to the following three-level cascaded framework, as illustrated in Figure 5(a), (b), and (c), respectively.
Level 1 (L1-Net) is a Fully Convolutional Network (FCN) [6-8]. The coefficients of FCN are not dependent on the dimensions of the input image. Level 2 (L2-Net) is an in-depth network, and deploys a fully connected layer before a classification or regression layer. Optimal performance is achieved from a complex network. Level 3 (L3-Net) is like L2-Net, but it increases the depth to get better performance. The final leaf disease detection results are obtained after passing through L3-Net.

Training the three-level cascaded network is trained separately [7]. Each level leverages two tasks to train: classification and bounding box regression. And each has two sibling output layers accordingly. One outputs a probability distribution, $p=(p_0, p_1 \ldots p_k)$ for k+1 classes. The other outputs are bounding box regression offsets, $t^k = (t^k_x, t^k_y, t^k_w, t^k_h)$ for each of the predicted object proposals. A multi-task loss function L defined by Equation (1) is used.

$$L(p,k^*,t,t^*) = L_{cls}(p,k^*) + \lambda[k^* \geq 1]L_{loc}(t,t^*) \tag{1}$$

Where k^* denotes the index of the class. And λ(.) is an indicator function, which ensures the bounding-box regression loss is calculated only for positive samples. L_{cls} and L_{loc} are loss functions for classification and bounding box regression, respectively. We use cross-entropy log loss Lcls $(p, k^*) = -\log p_k$ for the classification loss function, and use Euclidean loss $L_{loc}(t,t^*) = \| t-t^* \|^2$ for bounding box regression, where t and $t^*$are proposal box and ground-truth box, respectively.
Since the proposed cascaded network is implemented as a fully convolutional network, it can be trained end-to-end by back-propagation and stochastic gradient descent (SGD). Specifically, given the historical update of weight vector V_t and the weight vector W_t at step t, the weight vector update at step'‘t+1’ can be calculated by
Specifically, weight updation ‘t+1’can be calculated using Equation (2).

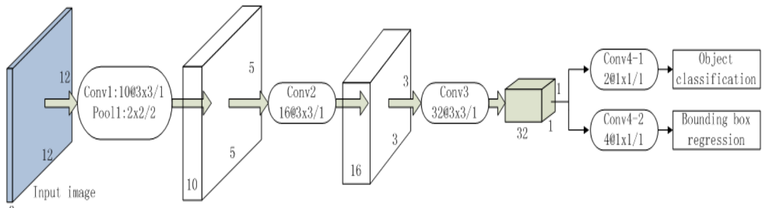
$$V_{t+1} = \mu V_t - \alpha \nabla L(W_t)$$
$$W_{t+1} = W_t + V_{t+1} \tag{2}$$

where the parameter α > 0 is known as the learning rate, and μ represents the momentum. The overall pipeline of the three-level cascaded CNN structure is shown in Fig..

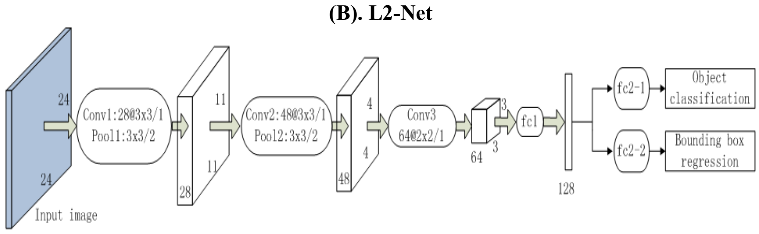
5. Methodology

Chlorophyll Index is used to evaluate the nitrogen status in a non-destructive manner. Nitrogen is necessary for the manufacture of amino acids, DNA, and ATP molecules. Without adequate nitrogen, plants cannot grow adequately as nitrogen forms the centre of the molecules in chlorophyll. Monitoring the nitrogen status depicts the health of the crops and their fertilizer requirements. The chlorophyll content, on the other hand, points out the formation of old cells over a period, which are formed due to the plant stress and disease outbreak.
The experimental validation proves the efficiency of the AI model, illustrated in Figure 6. The images for the crops undergoing plant stress are gathered from the kaggle database (https://www.kaggle.com/datasets/emmarex/plantdisease?select=PlantVillage). Sample images of the diseased and healthy plant leaves are displayed in Figure 7. Various diseases like BS, EB, LB, MD, LS, SM, TS, and YLC attack the Bell Pepper, Potato, and Tomato plants, causing retardation in plant growth, thereby offering stress to the plants. The images are pre-processed, and the Augmentation process is carried out, followed by splitting the train/test data set. CNN is used as a classifier for plant disease detection. The various diseases that are to be predicted and detected by the CNN architectures are early/late blight, bacterial spot, mold, spider mite, and yellow leaf curl. Finally, evaluation is carried out using various performance measures like True negative (TN), True positive (TP), False positive (FP), and False Negative (FN) along with Model's Accuracy (ACC), Precision (P), Sensitivity (Sn), Specificity (Sp), and F-score.

(A). L1-Net



(B). L2-Net



(C). L3-Net

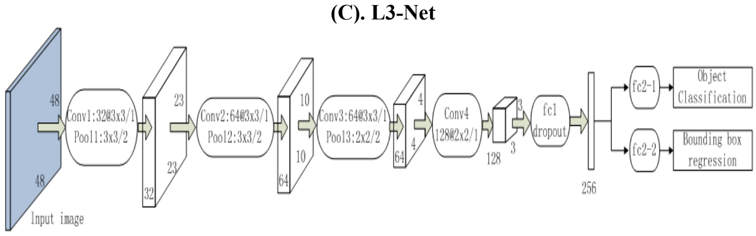


Fig. 5: The Architectures of Cascaded CNNS.

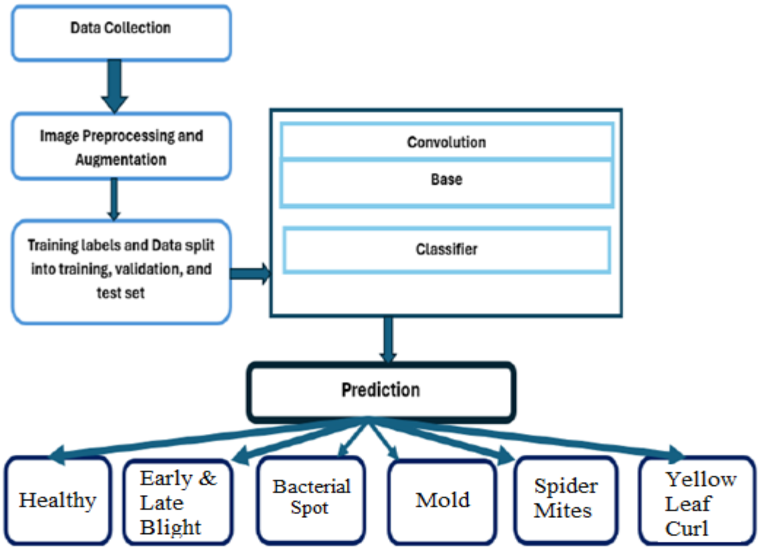
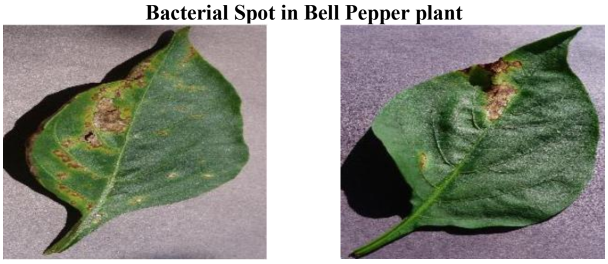
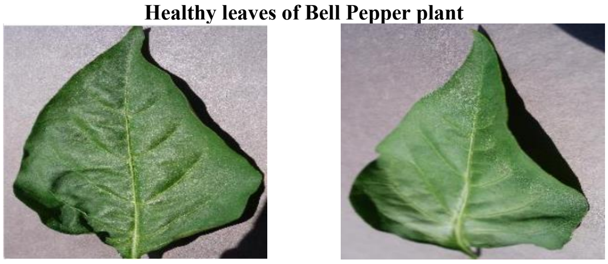


Fig. 6: General Block Diagram for AI Based Prediction of Plant Diseases and Chlorophyll Deficiency.

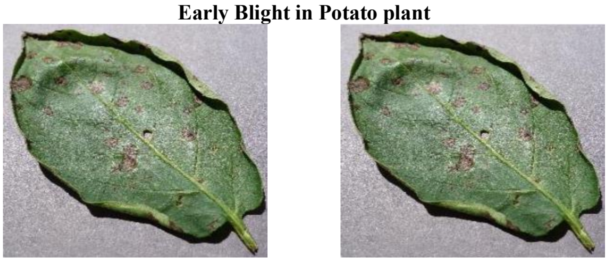
Bacterial Spot in Bell Pepper plant



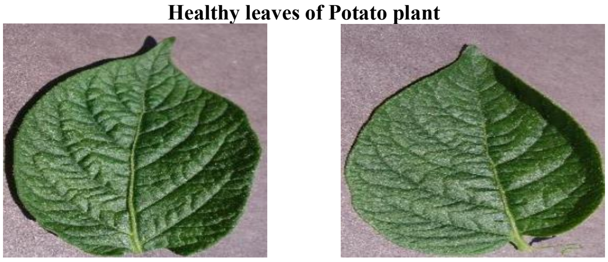
Healthy leaves of Bell Pepper plant



Early Blight in Potato plant

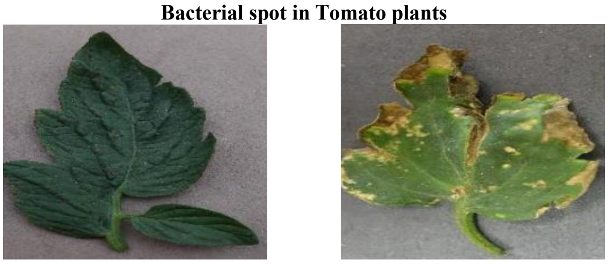


Healthy leaves of Potato plant



Late Blight in Potato plant

Bacterial spot in Tomato plants



Early Blight in Tomato plants

Late Blight in Tomato plants

Mold in Tomato plants

Leaf spot in Tomato plants

Spider mites in Tomato plants **Target spot in Tomato plants**

Yellow Leaf curl in Tomato plants **Healthy leaves of Tomato plant**

Fig. 7: Sample Images of Diseased and Non-diseased plant leaves

6. Results and discussion

6.1. Pre-processing

There is a need for image pre-processing before the input of data into the training model. Some preprocessing steps that need to be carried out include: Normalization: it is the normalization of pixel values to get rid of heterogeneity between images. Denoising: This is the removal of noise in images by filters such as Gaussian blurring. Resizing: the resizing of the images into fixed sizes, for example, 224 x 224 pixels, so that they feed into the CNN models. Data Augmentation includes methods like rotating, flipping, and zooming to avoid over-fitting/make a robust model.

6.2. Feature extraction

Leaf disease Feature Extraction: It is possible to train the model on the diseased and non-diseased leaf images to detect features, meaning colour changes, wrinkles, and architectural distortions. Feature extraction can be done using pre-trained models, for example, ResNet-50, and further fine-tuned on the Kaggle agricultural leaf dataset.

6.3. Convolutional neural network (CNN)

The Feature Extraction for non-diseased and disease-affected leaves in the plant, the CNN will extract morphological features from the leaf surface by identifying the patterns that may point towards leaf diseases. For this task, pre-trained models such as InceptionV3 or EfficientNet are applied. In the hybrid Layer, two separate CNN models can be fused to increase the classification efficiency. The output from the two CNN models is fused in the hybrid layer, where both non-diseased and disease-affected leaves in the plant images are considered by the model to perform an enhanced analysis.

6.4. Model architecture

The basic framework contains convolutional layers, Pooling layers, Fully Connected Layers, a fusion layer, and a classification layer or output layer, as illustrated in Figure 8 with a simple block diagram. The Convolutional Layers are used for the extraction of features for both non-diseased and disease-affected leaves in the plants. Pooling Layers are used to reduce the dimensions while stopping over-fitting. Fully Connected Layers facilitate the combination process and initiate further computations based on the learnt features to predict the nature of the leaf disease and its size. The Fusion Layer is a concatenation layer that will combine features generated from both images. This ensures that this combination allows for better predictive capabilities in the model. Classifier is a softmax or multi-class classifier that will classify the plant diseases respectively, and a regression that estimates the size of the affected area of the leaves.

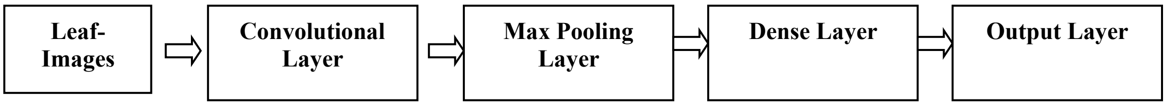


Fig. 8: Basic Architecture of CNN.

6.5. Evaluation metrics

Accuracy: Overall accuracy for diseased and non-diseased plant classification cases.
Precision, Recall, and F1-Score: These are to be used as performance metrics to check how well the model is performing, mainly on the side of how it could identify diseased plants with a high recall, with precision not too high while giving false positives.
AUC-ROC: Area Under the Receiver Operating Characteristic Curve will evaluate how well the system can classify positive versus negative cases.
IoU (Intersection over Union): This metric will be applied for checking the leaf segmentation precision when computing the size of the affected leaf area. True negative (TN) represents the diseased leaves that are classified accurately. True positive (TP) indicates the non-diseased/healthy leaves that are classified accurately. False Positive (FP) represents the diseased leaves that are misclassified as healthy leaves. False Negative (FN) represents the non-diseased/healthy leaves misclassified as diseased leaves [47]. Additional evaluation matrices can be created to assess the Model's accuracy (ACC), Precision (P), Sensitivity (Sn), Specificity (Sp), and Intersection Over Union (IOU). These performance metrics can be calculated using Equations (3)–(7) [48 -50]:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$P = \frac{TP}{(TP+FP)} \tag{4}$$

$$Sn = \frac{TP}{(TP+FN)} \tag{5}$$

$$Sp = \frac{TN}{(TN+FP)} \tag{6}$$

$$I(B_p, B_A) = IOU = \frac{\text{area}\,(B_p \cap B_A)}{\text{area}(B_p \cup B_A)} \tag{7}$$

Table 2: Training Results for Various AI Algorithms

	CNN	RCNN	FRCNN	Cascaded CNN
Sensitivity	5	87	66	94
Specificity	10	72	85	91
Accuracy	53	59	76	93
Loss Rate	4	2	3	1
IOU	0.5	0.8	0.72	0.9

7. Conclusion

Naked eye inspection for plant disease identification is a very tedious process and is subject to errors. With the development of AI, fast diagnosis for pathogens affecting plants is classified and diagnosed. Machine Vision techniques are implemented in agriculture automation to monitor the plant's growth rate, plant diseases, and methods of prevention and fruit harvest. Voluminous datasets are needed to automate the agricultural process. Robustness, coordination, generalization, economization, and automation of agricultural systems will be enhanced shortly, thereby increasing the agricultural yield.
Summing up together, it is inferred that computerized machine vision technology is extensively deployed for offering solutions to agriculture-related challenges, thereby initiating developments in agricultural technology with an aim to increase the yield and superior agricultural products to society, enabling secure food consumption by the population. As an innovation in agricultural production and administration, an expertise suggestion can be provided to the farmers using dedicated simulation packages developed for the purpose of providing steadfast forecasts in the field of agriculture. Deep learning algorithms, the state-of-the-art technology, can be incorporated with the conventional image processing techniques to endorse computer vision technology applications and developments. This move towards smart agriculture can lead to the expansion of the agriculture domain by integrating this field with automation technology, which uses intelligent tools and structures. As a prospect, the machine vision technique with applied AI in agronomy plays an essential role in automating the increase of agricultural products with quality, to promote growth and development economically with improved efficiency and safety.

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