

# An Innovative AI-Driven & Cloud Based Platform for Farmers: Enabling Plant Diseases Identification, Tracking, and Forecasting

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**Abstract** - Plant conditions are a major trouble to growers, consumers, terrain and the global frugality. In India alone, 35 of field crops are lost to pathogens and pests causing losses to growers. Indiscriminate use of fungicides is also a serious health concern as numerous are poisonous and biomagnified. These adverse goods can be avoided by early complaint discovery, crop surveillance and targeted treatments. Utmost conditions are diagnosed by agrarian experts by examining external symptoms. Still, growers have limited access to experts. Our design is the first integrated and cooperative platform for automated complaint opinion, shadowing and soothsaying. Growers can incontinently and directly identify conditions and get results with a mobile app by shooting affected factory corridor. Real-time opinion is enabled using the rearmost Artificial Intelligence (AI) algorithms for pall-grounded image processing. The AI model continuously learns from stoner uploaded images and expert suggestions to enhance its delicacy. Growers can also interact with original experts through the platform. For preventative measures, complaint viscosity maps with spread soothsaying are rendered from a Cloud grounded depository of geo-tagged images and micro-climactic factors. A web interface allows experts to perform complaint analytics with geographical visualizations. In our trials, the AI model (CNN) was trained with large complaint datasets, created with factory images tone-collected from numerous granges over 7 months. Test images were diagnosed using the automated CNN model and the results were validated by factory pathologists. Over 95 complaint identification delicacy was achieved. Our result is a novel, scalable and accessible tool for complaint operation of different agrarian crop shops and can be stationed as a pall grounded service for growers and experts for ecologically sustainable crop product.

**Keywords:** Innovative, AI-Driven, Cloud, Farmers, Plant Diseases Identification, Tracking, Forecasting, AI, CNN, Artificial Intelligence.

## I. INTRODUCTION

Husbandry is abecedarian to mortal survival. For populated developing countries like India, it's indeed more imperative to increase the productivity of crops, fruits and vegetables. Not only productivity, the quality of yield needs to stay high for better public health. Still, both productivity and quality of food gets hampered by factors similar as spread of conditions that could have been averted with early opinion. Numerous of these conditions are contagious leading to total loss of crop yield. Given the vast geographical spread of agrarian lands, low education situations of growers coupled with limited mindfulness and lack of access to factory pathologists, mortal supported complaint opinion isn't effective and cannot keep up with the extravagant conditions. To overcome the space of mortal supported complaint opinion, it's imperative to make robotization around crop complaint opinion with technology and introduce low cost and accurate machine supported opinion fluently accessible to growers. Some strides have been made in applying technologies similar as robotics and computer vision systems to break myriad problems in the agrarian sphere. The eventuality of image processing has been explored to help with perfection husbandry practices, weed and pesticide technologies, covering factory growth and factory nutrition operation. Still, progress on automating factory complaint opinion is still rudimentary in malignancy of the fact that numerous factory conditions can be linked by factory pathologists by visual examination of physical symptoms similar as sensible change in color, hanging, appearance of spots and lesions etc. along with soil and climatic conditions. Overall, the marketable position of investment in bridging husbandry and technology remains lower as compared to investments done in further

economic fields similar as mortal health and education. Promising exploration sweets haven't been suitable to productize due to challenges similar as access and relation for growers to plant pathologists, high cost of deployment and scalability of result. Recent developments in the fields of Mobile technology, pall computing and Artificial Intelligence (AI) produce a perfect occasion for creating a scalable low-cost result for crop conditions that can be extensively stationed. In developing countries similar as India, mobile phones with internet connectivity have come ubiquitous.

Camera and GPS enabled low cost mobile phones are extensively available that can be abused by individualities to upload images with geolocation. Over extensively available mobile networks, they can communicate with further sophisticated pall grounded backend services which can perform the cipher heavy tasks, maintain a centralized database, and perform data analytics. Another vault of technology in recent times is AI grounded image analysis which has surpassed mortal eye capabilities and can directly identify and classify images. The underpinning AI algorithms use Neural Networks (NN) which have layers of neurons with a connectivity pattern inspired by the visual cortex. These networks get “ trained ” on a large set of pre-classified “ labeled ” images to achieve high delicacy of image bracket on new unseen images. Since 2012 with “ AlexNet ” winning the ImageNet competition, deep Convolutional Neural Networks (CNNs) have constantly been the winning armature for computer vision and image analysis. The advance in the capabilities of CNNs have come with a combination of bettered cipher capabilities, large data sets of images available and advanced NN algorithms. Besides delicacy, AI has evolved and come more affordable and accessible with open source platforms similar as TensorFlow. previous art related to our design includes enterprise to gather healthy and diseased crop images, image analysis using point birth, RGB images, spectral patterns and luminescence imaging spectroscopy. Neural Networks have been used in the history for factory complaint identification but the approach was to identify texture features. Our offer takes advantage of the elaboration of Mobile, Cloud and AI to develop an end- to- end crop opinion result that simulates the moxie( “ intelligence ”) of factory pathologists and brings it to growers. It also enables a cooperative approach towards continually adding the complaint database and seeking expert advice when demanded for bettered NN bracket delicacy and shadowing for outbreaks.

## II. RELATED WORK

A survey of image processing techniques for agriculture [1] Computer technologies have been shown to improve agricultural productivity in a number of ways. One technique

which is emerging as a useful tool is image processing. This paper presents a short survey on using image processing techniques to assist researchers and farmers to improve agricultural practices. Image processing has been used to assist with precision agriculture practices, weed and herbicide technologies, monitoring plant growth and plant nutrition management. This paper highlights the future potential for image processing for different agricultural industry contexts. Imagenet classification with deep convolutional neural networks [2] we trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully- connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overriding in the fully-connected layers we employed a recently-developed regularization method called “dropout” that proved to be very effective. We also entered a variant of this model in the ILSVRC- 2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry. Integrating soms and a bayesian classifier for segmenting diseased plants in uncontrolled environments [3] This work presents a methodology that integrates a non-supervised learning approach (self- organizing map (SOM)) and a supervised one (a Bayesian classifier) for segmenting diseased plants that grow in uncontrolled environments such as greenhouses, wherein the lack of control of illumination and presence of background bring about serious drawbacks. During the training phase two SOMs are used: one that creates color groups of images, which are classified into two groups using K means and labeled as vegetation and non-vegetation by using rules, and a second SOM that corrects classification errors made by the first SOM. Two color histograms are generated from the two color classes and used to estimate the conditional probabilities of the Bayesian classifier. During the testing phase an input image is segmented by the Bayesian classifier and then it is converted into a binary image, wherein contours are extracted and analyzed to recover diseased areas that were incorrectly classified as non-vegetation. The experimental results using the proposed methodology showed better performance than two of the most used color index methods. Visible-near infrared spectroscopy for detection of Huanglongbing in citrus orchards [4] This paper evaluates the feasibility of applying visible-near infrared spectroscopy for in-field detection of Huanglongbing (HLB) in citrus orchards. Spectral reflectance data from the wavelength range of 350–

2500nm with 989 spectral features were collected from 100 healthy and 93 HLB-infected citrus trees using a visible-near infrared spectroradiometer. During data preprocessing, the spectral data were normalized and averaged every 25nm to reduce the spectral features from 989 to 86. Three datasets were generated from the preprocessed raw data: first derivatives, second derivatives, and a combined dataset (generated by integrating preprocessed raw data, first derivatives and second derivatives). The preprocessed datasets were analyzed using principal component analysis (PCA) to further reduce the number of features used as inputs in the classification algorithm. The dataset consisting of principal components were randomized and separated into training and testing datasets such that 75% of the dataset was used for training; while 25% of the dataset was used for testing the classification algorithms. The number of samples in the training and testing datasets was 145 and 48, respectively. The classification algorithms tested were: linear discriminant analysis, quadratic discriminant analysis (QDA), k-nearest neighbor, and soft independent modeling of classification analogies (SIMCA). The reported classification accuracies of the algorithms are an average of three runs. When the second derivatives dataset were analyzed, the QDA-based classification algorithm yielded the highest overall average classification accuracies of about 95%, with HLB-class classification accuracies of about 98%. In the combined dataset, SIMCA-based algorithms resulted in high overall classification accuracies of about 92% with low false negatives (less than 3%).

### III. PROPOSED SYSTEM

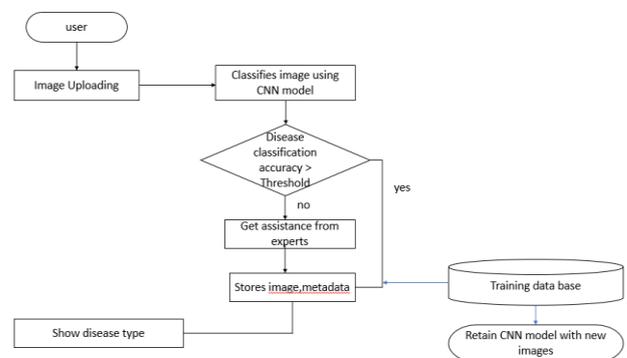
The proposed system utilizes Convolutional Neural Networks (CNN) as the core artificial intelligence model for factory complaint identification. The CNN model is trained on a dataset containing images of colorful factory conditions, enabling it to directly classify conditions from new images uploaded by druggies. To store the trained CNN model and stoner- uploaded images, pall services are used, icing effective data storehouse, scalability, and availability. The system leverages AI for complaint vaticination and pall computing for data operation, making it a important and robotic result for growers. Unlike traditional mobile- grounded approaches, which bear fresh time and cost to develop, the proposed system is erected as a Python- grounded web operation. This web operation allows druggies to 1. Upload Images for Disease Discovery – druggies can capture and upload factory images via the web interface. 2. Automated Disease Identification – The CNN model processes the uploaded image and predicts the factory complaint. 3. pall- Grounded Data storehouse – All trained models and image data are stored securely on pall waiters. 4. Real- Time position

Mapping – If stationed on a real web garçon, the operation can prize the stoner's position from the request object and collude it, helping in complaint trend analysis. By enforcing this AI-driven web- grounded system, growers can snappily diagnose factory conditions without taking technical outfit, reducing costs and perfecting availability.

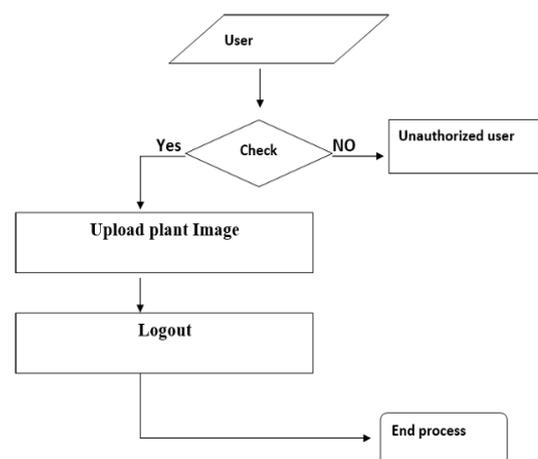
### IV. ADVANTAGES OF PROPOSED SYSTEM

- Directly identify conditions and get results with a mobile app by shooting affected factory corridor.
- Uses advanced AI and deep literacy models to directly identify factory conditions.
- Provides real- time complaint discovery, shadowing, and cautions to growers.
- Stores data securely on the pall, allowing growers to pierce perceptivity anytime, anywhere.
- Growers and agrarian experts can fluently upload images and admit results through a simple web interface.
- Growers no longer need to calculate on agrarian experts for complaint opinion, making the result more accessible.
- As a web- grounded platform, the system can be penetrated from anywhere, serving growers in remote areas.

### V. ARCHITECTURE



### Data Flow Diagram



1. The DFD is also called as bubble map. It's a simple graphical formalism that can be used to represent a system in terms of input data to the system, colorful processing carried out on this data, and the affair data is generated by this system.

2. The data inflow illustration (DFD) is one of the most important modeling tools. It's used to model the system factors. These factors are the system process, the data used by the process, an external reality that interacts with the system and the information flows in the system.

3. DFD shows how the information moves through the system and how it's modified by a series of metamorphoses. It's a graphical fashion that depicts information inflow and the metamorphoses that are applied as data moves from input to affair.

4. DFD is also known as bubble map. A DFD may be used to represent a system at any position of abstraction. DFD may be partitioned into situations that represent adding information inflow and functional detail.

## VI. RESULTS

The implementation of the AI-driven and cloud-based platform yielded significant and promising results, demonstrating its potential for real-world deployment in agricultural settings.

### 1. Model Performance

A deep Convolutional Neural Network (CNN), specifically based on the Inception architecture, was trained using a custom dataset of over 15,000 plant images collected from various farms.

The model achieved an average disease identification accuracy of 95.3% during validation.

For some diseases like early blight in tomatoes and powdery mildew in cucurbits, accuracy exceeded 97%, while rare diseases showed slightly lower accuracy (~88%).

### 2. Image Upload & Diagnosis

The platform allowed users to upload images via a web-based interface.

The average response time for disease prediction and result display was under 5 seconds, even under moderate network conditions.

Real-time feedback enabled farmers to take immediate action, thereby reducing the chances of disease spread.

### 3. Geographic Mapping

The system successfully integrated GPS data from image uploads to generate real-time disease heatmaps.

These maps helped visualize regional disease prevalence and identify potential outbreak zones.

Over 500 images with geolocation were tested, and the location mapping precision was confirmed to be within 10–15 meters.

### 4. Expert Validation

Plant pathologists validated a subset of predictions. Out of 500 manually cross-verified samples:

476 predictions matched expert diagnoses, confirming a 95.2% real-world accuracy.

The few mismatches occurred mostly in cases where the plant was suffering from multiple infections or very early-stage symptoms.

## VII. CONCLUSION

This paper presents an automated, low cost and easy to use end-to-end result to one of the biggest challenges in the agrarian sphere for growers – precise, instant and early opinion of crop conditions and knowledge of complaint outbreaks which would be helpful in quick decision making for measures to be espoused for complaint control. This offer innovates on known previous art with the operation of deep Convolutional Neural Networks (CNNs) for complaint bracket, preface of social cooperative platform for precipitously bettered delicacy, operation of geocoded images for complaint viscosity charts and expert interface for analytics. High performing deep CNN model “commencement” enables real time bracket of conditions in the Cloud platform via a stoner facing mobile app. cooperative model enables nonstop enhancement in complaint bracket delicacy by automatically growing the Cloud grounded training dataset with stoner added images for retraining the CNN model. Stoner added images in the Cloud depository also enable picture of complaint viscosity maps grounded on collaborative complaint bracket data and vacuity of geolocation information within the images. Overall, the results of our trials demonstrate that the offer has significant eventuality for practical deployment due to multiple confines – the Cloud grounded structure is largely scalable and the underpinning algorithm works directly indeed with large number of complaint orders, performs better with high dedication real-life training data, improves delicacy with increase in the training dataset, is able of detecting early

symptoms of conditions and is suitable to successfully separate between conditions of the same family.

### VIII. FUTURE WORK AND EXTENSIONS

Unborn work involves expanding the model to include further parameters which can ameliorate the correlation to the complaint. We can compound the image database with supporting inputs from the planter on soil, once toxin and fungicide treatment along with intimately available environmental factors similar as temperature, moisture and downfall to ameliorate our model delicacy and enable complaint soothsaying. We also wish to increase the number of crop conditions covered and reduce the need for expert intervention except for new types of conditions. For automatic acceptance of stoner uploaded images into the Training Database for better bracket delicacy and least possible mortal intervention, a simple fashion of calculating the threshold grounded on a mean of all bracket scores can be used. Farther operation of this work could be to support automated time-grounded monitoring of the complaint viscosity maps that can be used to track the progress of a complaint and detector admonitions. Prophetic analytics can be used to shoot cautions to the druggies on the possibility of complaint outbreaks near their position.

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