

Deep Convolution Neural Network Based solution for Detecting Plant Diseases

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Abstract

More over 58 percentage of the population works in agriculture, which accounts for more than 20 percent of India's total GDP. This research concentrates on plant diseases because they pose a serious danger to small-scale farmers' livelihoods and food production. In conventional farming, skilled employees are used to visually inspect each row in order to identify plant diseases. This labor-intensive, time-consuming task is inherently fault because it is carried out by humans. The purpose of this study is to create an automated detection model for the three most common maize plant diseases Frequent Rust, Cercospora Spot, and Northern Leaf Blight by combining image recognition and deep learning methods (Faster R-CNN+ResNet50) to evaluate real-time photos. The suggested system effectively identified three maize diseases with a 93.5% accuracy rate.

Keywords: Disease detection; real-time images; maize disease; deep-convolution neural network.

I. INTRODUCTION

More over 58 percent of the total population is employed in agriculture, which accounts for more than 20 percent of India's total GDP. In India, more than 70 percent of rural small households depend on agriculture [1]. The Continual growth in India's population has increased the demand for food, resulting in a situation where crop production is insufficient to meet the demand. The major factors which reduce food production are climatic changes, plant diseases, weeds, and so on. This research concentrates on plant diseases because they pose a serious danger to food production and small-scale farmers' ability to make a living. To avoid disease-related yield loss, a variety of approaches have been developed, whereas to avoid epidemics, a preventive method at the seedling stage is insufficient, but strict visual monitoring is required for early disease detection in the crop. In conventional farming, skilled employees are used to visually inspect each row for signs of plant disease. This labor-intensive, time-consuming task is potentially fault because it is carried out by humans. Furthermore, particularly in separated and poor communities, plant biotechnology specialists are not always readily available. To concentrate on this issue, researchers developed a number of solutions based on the introduction of new technologies like image processing, computer vision, object detection and classification, and so on for crop quality assessments.

Precision farming is the new Agricultural Evolution that uses science and technology to increase crop production, which strives to reduce pesticide and fertilizer use, while also lowering farm costs. Precision farming has proven benefits in several agricultural areas as it transitions from traditional methods to new ways. It entails strategies for efficiently detecting and curing diseases or pests by accurately focusing the amount of fertilizers or insecticides required. Precision farming's main objective is to obtain real-time data in order to boost agricultural productivity and maintain crop quality. Sensors and remote sensing, high precision positioning systems, mapping and surveying, Automated steering systems mapping, Global navigation satellite systems, variable-rate, and computer-based applications are some of the technologies utilized in precision agriculture. Drone's integration into precision farming operations has completely altered the market landscape. The Drone may be used in farming for a number of functions, such as sowing seeds, applying pesticides and fertilizers, and monitoring crop growth. A drone must be with a camera, a spraying, and pesticide/fertilizer canisters in order to do these tasks. Drones can be employed to regularly check on the health of crops and spot any irregularities at an early stage. To determine overall crop growth patterns &

approximate the yield, the Drone acquired data will be processed in real-time with the help of a video/image analytics system based on deep learning or machine learning technology.

The goal of this work is to create an automated detection algorithm that analyzes real-time photos taken by a basic camera in order to identify and categorize the three prevalent maize plant diseases using a variety of image processing & deep learning approaches. Northern Leaf Blight, Common Rust, and Cercospora leaf spots. Maize is India's third-largest food crop, after rice and wheat. Maize is a staple food for the human-being, as well as primary raw material to thousands of industrial goods, including oil, starch, alcoholic beverages, pharmaceutical, food sweeteners, cosmetics, textile, film, gum, paper, and package sectors. Maize is farmed throughout the year in all states for fodder, grain, sweet corn, green cobs, pop corn and baby corn in peri-urban areas. Andhra Pradesh, Uttar Pradesh, Himachal Pradesh, Karnataka, Bihar, Rajasthan Maharashtra, Madhya Pradesh, are the leading states that grow maize, supplying over 80 percent of India's total maize production [2]. Diseases and pests that found in fields can easily infect maize. Abiotic (non living) and biotic (living) agents are the two types of agents that can affect maize plants. Bacteria, Insects, Viruses, and fungi are examples of living agents. Various environmental factors such as excess moisture, rapid temperature change, high humidity conditions, poor soil pH, and insufficient nutrients are examples of non-living agents.

1.1 Problem Statement

The problem discussed in this study is detecting anomalies in cultivated land, particularly in the recognition & categorization of maize diseases. Plants are articulated bodies in general; nevertheless, defining a single model that detects and distinguishes different diseases and plants could be difficult. Because of their non-rigid structure, crop growth is not uniform, and intra-class variability between crops is enhanced. The research focuses on applying deep learning approaches to develop disease detection and classification models that capture the prominent features of diseases and distinguish them from other items of interest, such as crops.

Mathematical statement is as follows,

$$Y_{out} = \text{for} \begin{cases} X[I] & \mathbf{0} \text{ if disease} \\ & \mathbf{1} \text{ if normal} \end{cases} \rightarrow (1)$$

$X[I]$: Maize leaf images as input
 $Y_{out} = 0$ if leaf has a disease
 $Y_{out} = 1$ if leaf is healthy

1.2 Objectives

- To propose a more appropriate deep learning model for detecting diseases in maize plants, specifically Northern Leaf Blight, Common Rust, and Cercospora Leaf Spot using 1269 images obtained with various resolutions by camera devices at early and late stages and fed to deep detector: Faster R-CNN (Faster Region-based Convolutional neural-network).
- To recognize maize diseases, integrate deep learning model plus “deep feature extractor”: ResNet50.
- To train and test the proposed system from start to end on the maize disease dataset described in this paper, which includes challenging photos of several maize diseases, as well as intra- and extra-class variations.

The following is a summary of the rest of the paper: Section 2 studies the influence in this field, Section 3 explains the methodology, Section 4 presents the evaluated results, & Section 5 provides the conclusion of the work.

II. LITERATURE SURVEY

This section summarizes the results of numerous studies in plant diseases and pests detection in deep learning technology. Deep learning offers a lot of potential for classifying plant diseases severity automatically. In [3], the authors gathered a 1090 comprehensive real-time image dataset of tomato leaves infected by four diseases (Septoria Leaf spot, Leaf curl, Septoria, Bacterial Spot, and Early Blight), where images have been captured by camera devices with various resolutions (64MP, 32MP), different lighting conditions, and all stages of tomato disease (early, medium, and final) and fed into a deep learning model detector: Faster R-CNN plus “deep feature extractor”: ResNet50 to recognize tomato diseases. Faster R-CNN with ResNet50 was identified as a viable approach to identify the type and location in tomato plants disease. Also, they trained and evaluated the deep learning system from start to end on the tomato disease dataset described in their paper, which includes complex photos of various tomato diseases, as well as extra- and intra- class variations.

The author of [4] used the Plant Village dataset to extract photos of tomato leaves. There are 14828 photos are grouped into nine diseases in the dataset. The author used CNN as a learning technique to train classifier, which allows for the direct usage of images and avoids the use of hand-crafted features. Visualization methods were used to analyze the deep models (Google Net and AlexNet) in order to fully understand symptoms and locate diseased areas in the leaf. The Plant Village dataset's

photos were captured in a lab. under controlled conditions, which is a flaw in this model.

The authors [5] developed a CNN model to detect tomato diseases and pests based on VGG16+Transfer learning. The authors created an image dataset with 11 categories totalling 7040 photos, each disease with 640 photos. The (VGG16+SVM) technique uses VGG16 as a picture collector & integrates it with a SVM classifier to identify diseases and pests in tomato photos. End to end classification system was developed by using fine tuning method. The overall maximum performance, on the other hand, is dependent on substantially higher quality test images, rather than low-quality test images.

In [6] the authors collected 5000 images from different farms in Korean Peninsula. The authors aim to build a deep-learning system for detecting and recognizing the disease and pest types and where anomalies are located in images. For the purpose the authors built an, Meta architectures R-FCN (Region-based Fully Convolution Network), Faster R-CNN (Faster Region-based Convolution Neural Network), and SSD (Single Shot Multi box Detector) and various deep feature extractors (VGG net, Res Net) are considered to detect and classify pests and diseases in maize leaf images. In addition, to improve accuracy and reduce FP's (false positives), data augmentation, global and local class annotation methods were used during the training stage, which is trained and tested with Tomato Pests and Diseases Dataset. The system is capable of detecting nine distinct types of pests and diseases. Because there aren't enough samples, some classes with a lot of pattern variation get mixed up with others, resulting in false positives.

The authors in [7] used a diverse dataset that includes images from the nursery, Plant Village dataset, and farm. Convolutional Neural-Network was trained to identify 3 diseases. Using the Soft max activation function, a classification model was used to calculate the class confidence score. All of the feature maps from the preceding layers are entirely connected by fully connected layers and classifies images into 3 diseases (powdery mildew, downy mildew, and early blight). Remarks: Images in the Plant Village dataset are collected under a controlled condition which holds a drawback of the model. The authors of [8] considered a tomato dataset that included 500 photos from nearby farms and 2100 photos from the internet. In order to classify tomato disease photos into good, bad, average types, Google's Inception Model was retrained with transfer learning and in turn, increased system execution speed.

In their work [9], the authors examined 1,796 photos of maize leaves, with 768 photos of non-infected leaves, and 1,028 NLB (Northern Leaf Blight) infected photos. The authors built a technique that can identify NLB disease automatically in maize plants photos. In order to detect early stage of NLB disease regions in photos, several CNN's are trained with tiny parts of photos, and separate heat maps (with disease and healthy) are generated, which is fed to final trained CNN on entire photo to detect disease or not. Remarks: To train CNN, one should classify images manually, which is time-consuming and error prone.

The authors of [10] collected 3823 photos of maize disease leaves from the plant's website and annotated them for four different types of maize disease. Using AI methods such as Random Forest (RF), K-Nearest Neighbor (KNN), Decision Tree (DT), Support Vector Machine (SVM), Naive Bayes (NB), & the authors predicted early disease detection in crops. When compared to all other models, Random forest achieved 80.68 percent accuracy. Remarks: However, each model in the classification process has its own set of problems that may or may not apply to other available datasets.

III. METHODOLOGY

The approach for the proposed maize plants disease detection system is presented here. More appropriate deep learning architecture to detect diseases in maize plants using 1239 photos taken with varied resolutions using mobile phone camera at all stages (early, late) is fed to deep detector: Faster R-CNN (Faster Region-based Convolutional neural network), and combines with “deep feature extractor: Residual Network-50 (ResNet-50)”.

3.1 System Overview

The goal of this research is to detect three types of diseases i.e Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot, that impact maize plants by using Deep-Learning as the primary body to the projected system. Figure 3.1 depicts a high-level picture of the system. Each stage in proposed system is described in depth below.

3.2 Data Collection

Maize dataset has images of Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot diseases occurs in maize plants, which were collected using a simple phone camera under a variety of situations depends on place (e.g., nursery, farms), season (humidity, temperature), time (illumination), and we visited a number of maize fields in Piller, Mangapuram, and Kallur in Andhra Pradesh. The maize dataset includes information such as images with different resolutions (64MP, 32MP), the medium, last, and early infectious disease condition of maize leaves, images with a complex background (such as soil), and images in which the desired object (the disease) is only partially visible or overlapped with other objects (such as leaves or stems). The table (Table 3.2) summarizes the symptoms of Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot.

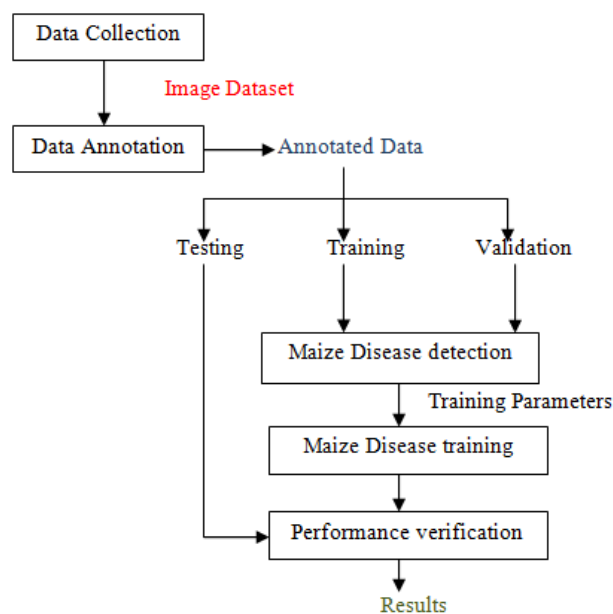





Figure 1 High-level picture of proposed system for maize disease detection

Table 1: Database For Infected Maize Samples For Disease Detection

Disease	Symptoms	Collected sample
Cercospora Leaf Spot	A little necrotic spot on the leaf that grows into a rectangular lesion as it ages and become browned and eventually grey.	
Common Rust	Small tan spots on lower and upper surfaces of leaves, as disease matures turns from dark brown to black	
Northern Leaf Blight	Elliptical gray-green lesions on leaves	

3.3 Data Annotation

Using the Labeling tool (which is a great tool for labeling pictures) manually marked disease regions in all images by bounding-box's and class type to which the disease belongs. The data annotation stage output is the coordinates of differing sized bounding boxes with their respective disease class, which will be evaluated by the IoU (Intersection-over-Union) with the proposed system and predicted result during testing.

3.4 Faster-RCNN Maize Disease Detection

The aim is to detect and identify three disease classes and their locations in maize plant images. To get accurate results from the system, the bounding boxes that include disease should be correctly defined to which the disease belongs. Faster R-CNN generates essential (Region of Interest) ROI's for maize disease detection using the Region Proposal Network (RPN).

Detecting maize diseases in images using a Faster RCNN method involves the following steps:

- 1 First, you'll need to provide the ConvNet with an image; it'll generate feature maps and deliver them to RPN.
- 2 Second, RPN generates a maize disease image with k fixed-size anchor boxes of varied sizes and shapes by sliding windows on the collected feature maps at each frame, thereby predicting the likelihood that an anchoring is disease and a boundary regressor to best suit the anchoring for disease.
- 3 After acquiring anchor boxes (object proposals) of varying sizes and shapes, and trimming each proposal so that it includes tomato illnesses, ROI collects fixed-size feature mappings to all the anchors.
- 4 Four, the gathered fixed-size feature mappings are sent to a fully connected layer that contains a softmax and a regression analysis layer. Finally, bounding-boxes to the discovered maize diseases are projected, and the diseases are categorized (Common Rust, Northern Leaf Blight, and Cercospora).

3.5 RPN training and loss functions

As a rule of thumb, a sample is considered "positive (illness)" if it falls into either of these two categories: For each ground truth-box, a) it has the highest Intersection over Union (IoU) value; and b) when the IoU value is greater than 0.5. Anchor is considered "negative" if the average IoU of all ground truth boxes is less than 0.5. (healthy)'. For RPN training, rest all anchors are ignored (either negative or positive). Each RPN mini-batch is made from a single image. In order to avoid bias learning, a batch should be formed with 128 healthy (negatives), 128 disease (positives) samples. The RPN training loss is estimated by:

$$L(\{p_i\}, \{t_i\}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*) \quad (2)$$

Here,

i - Index of anchor in mini-batch

$L_{cls}(p_i, p_i^*)$ - Classification loss is the log loss over two classes (disease v/s healthy)

p_i - Output score from the classification branch for anchor i

p_i^* - Ground truth label (1 or 0)

(t_i, t_i^*) - Regression loss

When anchor truly includes a disease, i.e., if ground truth p_i^* is 1, then the regression loss $L_{reg}(t_i, t_i^*)$ gets activate. The t_i refers to regression layer's output prediction, which is made up of 4 variables [t_x, t_y, t_w, t_h].

The t_i^* (regression target) is estimated by:

$$t_x^* = \frac{(x^* - x_a)}{w_a}, \quad t_y^* = \frac{(y^* - y_a)}{h_a}, \quad t_w^* = \log \frac{(w^*)}{w_a}, \quad t_h^* = \log \frac{(h^*)}{h_a} \quad (3)$$

Here,

h : bounding-box height

x^*, x_a : locations of the anchor box and the corresponding ground truth bounding box.

w : bounding-box width

(x, y) : beginning upper left corner of box

IV. EXPERIMENTS & RESULTS

The proposed system uses Faster R-CNN with ResNet-50 to detect three common maize diseases. Firstly, the proposed system's performance is evaluated using the Pascal VOC Challenge's [11] IoU (Intersection_over_Union) and AP (Average Precision).

$$IoU(A, B) = \left| \frac{A \cap B}{A \cup B} \right| \quad (4)$$

Here,

A – Annotated Coordinates of Ground-truth-box

B – Predicted result of the network

When the calculated IoU is more than 0.5 (the threshold value), the anticipated result is considered to be true positive (TP), otherwise it is considered to be false positive (FP) (FP). When few false positives (FPs) are generated from photos that show

diseased areas, the proposed technique is effective. IoU is a common method for evaluating the precision of an object detector. The AP for Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot in maize is the mean Average Precision (mAP), which is derived by averaging the precision for each recall level from [0, 0.1, ..., 1].

$$AP = \frac{1}{11} \sum_{r \in \{0, 0.1, \dots, 1\}} p_{\text{interp}}(r) \quad (5)$$

$$p_{\text{interp}}(r) = \max_{\tilde{r}: \tilde{r} \geq r} p(\tilde{r}) \quad (6)$$

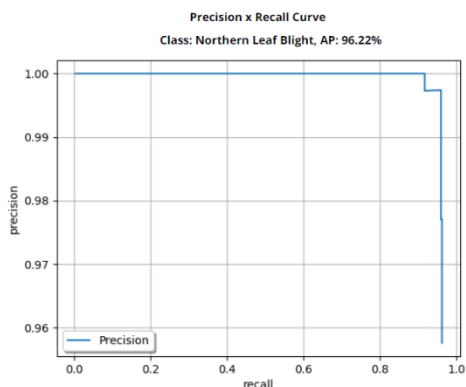
Where $p(\tilde{r})$ is the precision measure at \tilde{r} recall shown in Figure 5 for each maize disease. The mAP calculated for IoU = 0.5 and the proposed detection system achieved more than 91% Faster RCNN with ResNet50 results achieved for Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot maize diseases is shown in the Table 4. The proposed system mAP gave a performance more than 91%. The performance can be improved by exercising the system with extra samples. Tensorboard [12] is an tensorflow visualization toolkit provides visualization & tracking of whole loss, the Figure 4 shows the resulting loss curve for an fifty two thousand epoch's and shows that proposed is capable of learning maize data by achieving a smaller error-rate less than 0.1 at fifty one thousand epoch. The qualitative results achieved by the proposed system to detect three common maize diseases is shown in Figure 6.



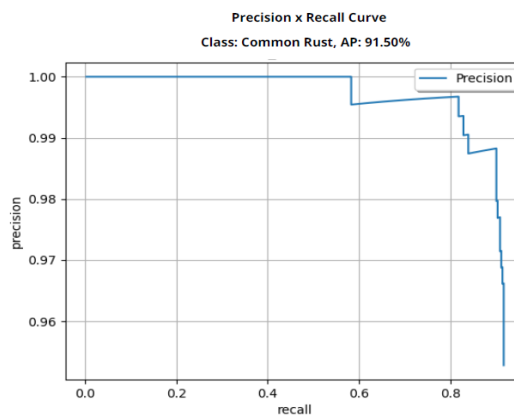
Figure 2: Total loss curve of our proposed system

Table 2: Proposed system results achieved for maize diseases

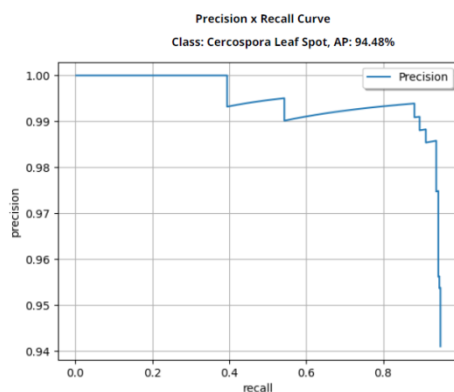
Class	ResNet50
Northern Leaf Blight	96.22%
Common Rust	91.50%
Bacterial Spot	94.48%
Total mean AP	94.06%



(a)



(b)



(c)

Figure 3: Precision x Recall curve for (a) Northern Leaf Blight (b) Common rust (c) Cercospora Leaf Spot



(a)

(b)

(c)

Figure 6: Qualitative results achieved by the proposed system
(a) Common rust (b) Cercospora Leaf Spot (c) Northern Leaf Blight

V. CONCLUSION

The goal of this research was to create a computerized detection model for three prevalent maize plant diseases using a mixture of image processing & deep learning approaches to analyze photos taken in real time by a cheap camera. Photos in 64MP, 32MP, and lower resolutions, as well as images with complicated backgrounds (like dirt) and images in which the target item (disease) is partially concealed, covered with another object (leaves, stems), only or midway in the image are all part of the maize dataset. The proposed system (Faster R-CNN+ResNet-50) successfully detects three common maize diseases and achieved 93.5% accuracy with an error-rate less than 0.1. Currently the proposed system detects maize diseases, further work can be extended to detect other plant diseases by training the proposed system with other disease dataset

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