Data Collection and Analysis Using IOT Device and Machine Learning Techniques for Disease Classification on Soybean Plant

Mr. Nitesh Rastogi[1] & Dr. Priya Swaminarayan[2]

[1]Research Scholar, Faculty of Engg. And Tech., Parul University, Gujarat, India

[2]Dean, Faculty of IT & Computer Science, Parul University, Gujarat, India

ABSTRACT Plant diseases result in considerable production and financial losses, as well as a reduction in the quality and quantity of agricultural goods. Plant disease identification is now being given more attention in the context of large-scale harvesting operations. Ranchers have challenges while transitioning from one infection preventive technique to the next. The typical methodology used in practice for detecting and differentiating proof of plant diseases is specialists' unassisted eye perception. Since CNNs have made notable contributions to the field of machine vision, this paper uses a convolution-neural-network (CNN) model and bespoke object detection to distinguish and analyze diseases in plants from their leaves and to count the number of pods in the soybean plant. Standard CNN models also necessitate a large number of boundaries, resulting in a larger calculation cost. We replaced traditional convolution with Efficient net in this study, which reduces the boundary number and calculation cost. The models were created using data from the Indian Institute of Soybean Research (ICAR) and web scraping, which included distinct plant species and illness classes. Using CNN (Convolution neural network) and EfficientNetB0, the models achieved illness characterization precision rates of 84% and 90%, respectively, which were significantly higher than that of traditional hand-tailored component-based approaches.

Keywords: Convolution neural network (CNN), Soybean leaf, Neural Network, Sensors.

I. INTRODUCTION

According to projections, the human population would reach 9 billion by 2050, with a 60% rise in food demand. As a result, enhancing and increasing the quality of crop yield is a primary focus. Infectious biotic and abiotic illnesses have recently reduced prospective yields by an average of 40%, with many farmers in developing countries reporting yield losses of up to 100%. Plant disease identification and treatment are a problem for farmers all over the world. With advances in precision agriculture technology, there have been a number of studies on plant disease categorization, albeit the results of the existing methodologies are not sufficient. Furthermore, earlier research, particularly in the field of image segmentation, has failed to accurately split leaf parts from the entire image. Furthermore, earlier attempts have failed to accurately separate the leaf section of a picture from the entire image, especially when the background is complex. In order to solve these issues, a computer vision solution is offered. Two elements make up the proposed strategy. The first module provides a convolution neural network (CNN) that uses deep learning to classify leaf diseases from a full image. The second module covers specialized object detection for detecting soybean pods and flowers. All of the tests are based on ICAR data. With strong precision, recall, and f1-score, the suggested model achieves identification accuracy of 84 and 90 percent. In agriculture, plant infections are a major concern. The development of an early reaction to avoid economic losses could be aided by precise and automatic identification of leaf diseases. Deep neural networks have been used in recent plant disease research. However, in such studies, the models have been employed as a black box, with the tagged images being passed via the networks.

II. BACKGROUND

Farmers have developed strategies for controlling weeds, insect pests, and diseases since the dawn of agriculture. Because pests and diseases have such a significant impact on human and animal health, it is critical for those interested in plants to gain a solid understanding of weed science, entomology (study of insects), and plant pathology (study of plant disease), as well as how to minimize losses caused by these important plant pests. Diseases and damage affect all plants, whether native and cultivated. Plant disease is defined in a variety of ways. Disease is defined as inadequate plant growth caused by a persistent irritant such as a pathogen (an organism capable of producing disease) or chronic exposure to less than ideal growing conditions. Injury, on the other hand, is the loss of plant vitality caused by a sudden occurrence such as a lightning strike, hail damage, chemical burn, or mechanical damage. Injuries are typically simple to detect due to their immediate and "cause-and-effect" nature. The impacts of diseases are brought on by a continuous process of irritation. The source of constant discomfort could be either abiotic (non-living) or biotic (alive) (caused by a pathogen). Because abiotic illnesses do not transfer from plant to plant, they are also known as noninfectious diseases. Nutrient deficits, as well as air contaminants like automotive pollution, can occur when plants are exposed to too much or too little light. Pathogens cause biotic illnesses, which are often referred to as infectious diseases because they can spread within and between plants. Plant pathogens, which include viruses, bacteria, fungus, and nematodes, are quite similar to those that cause disease in people and animals. Pathogens can infect leaves, shoots, stems, roots, fruit, and seeds, among other parts of the plant. A susceptible host, a pathogen capable of causing disease, and a favorable environment for the pathogen to proliferate is all required for an infectious disease to emerge. Disease will not occur if any of these elements are missing. When it comes to infectious plant diseases, measures that priorities plant growth above pathogen activity likely to reduce disease incidence. Plants that are properly fertilized and hydrated, for example, are less likely to develop illness. Whatever pathogen causes the disease, it must be able to: (a) come into contact with a susceptible host (inoculation); (b) gain entrance or penetrate the host through a wound, a natural opening on the plant surface (stomata, lenticels, etc.), or direct penetration of the host; (c) establish itself within the host; (d) grow and multiply within or on the host; and (e) spread to other susceptible plants. In the absence of a sensitive plant host, diseases must be able to endure long periods under harsh environmental circumstances. The illness cycle refers to all of these processes taken together. The disease will be less severe or will not develop if this cycle is stopped. Sign and symptom are two phrases that are frequently used when discussing plant disease and injury. The two terms are utilized differently in the medical profession than they are in the plant world. When a pathogen or portion of a pathogen is seen in or on an infected plant, the term sign is employed. Fungal hyphae or mycelium, spores, fruiting structures, bacterial cells, or virus particles are all examples. Symptoms are changes in a plant's appearance or behavior that occur as a result of illness or injury. Because disease symptoms take time to develop, they are generally undetectable early on after infection. Yellowing of the leaves, wilting of the leaves, and dropping of the leaves are all common symptoms. of leaves or fruit; and stunting of plant parts or the whole plan

Types of Soybean Leaf diseases

- **Soybean Rust**

Soybean rust is caused by the fungus Phakopsora pachyrhizi. Symptoms are most common after flowering, beginning on lower leaves. Lesions start to form on lower leaf surfaces as small, gray spots that change to tan or reddish-brown. Lesions are scattered within yellow areas appearing translucent if held up to the sun. One to many tiny pustules can be found on the lower leaf surfaces of mature lesions. In southern states, the rust pathogen persists. Movement northward is reliant on spore dissemination and disease establishment in new locations, a process that must be repeated numerous times over the course of a growing season for rust to become an epidemic in northern states. Cool, wet weather or high humidity favor epidemics. Dense canopies provide ideal conditions for disease development. Foliar fungicides are the only treatment option for soybean rust, and they must be used prior to infection or as soon as possible after infection.

- **Yellow Mosaic**

Mosaic in Yellow the potyvirus Soybean mosaic virus causes soybean mosaic. SMV has received far more research than bean pod mottle virus. Based on field surveys conducted from the 2000 to 2002 growing seasons, SMV is not as frequent as BPMV in Nebraska, with only 3.5 percent of fields sampled having SMV. SMV is spread through seed and aphid species. Seed transmission is less than 5% in most cultivars, but significantly higher than seed transmission for BPMV. Yield losses caused by SMV typically range from 8% to 35%, however losses as high as 94 percent have been reported. This disease also can be spread through soybean aphids which can vector this virus. SMV infection will reduce oil content, seed germination, and seed quality due to seed coat mottling. SMV symptoms vary depending on the variety, virus strain, climate, and age of the plant when it is infected. The majority of types will be stunted, with fewer pods.. Trifoliate leaves will have a mosaic of light and dark green areas that may become blistered or raised with time. Leaves may appear distorted, generally with the leaf margins curling downward. Symptoms are most severe during cool weather and infection is rarely evident during Nebraska summers. The length of time between infection and appearance of symptoms also varies with temperature. Seed from infected plants can be mottled black or brown depending on hilum color. Not all infected plants produce mottled seed and seed mottling does not indicate that the virus in present in the seed.

- **Bacterial blight**

Bacterial blight is a disease caused by bacteria. Bacterial blight is a prevalent soybean disease that thrives in cool, damp conditions. This disease normally manifests itself at low levels, causing no yield reduction. Bacterial blight is sometimes confused with septoria brown spot. The presence of a halo around bacterial blight lesions distinguishes the two illnesses. Both diseases can affect the same plant, although bacterial blight is more prevalent on young leaves, and brown spot is more common on the plant's older, lower leaves.

Bacterial blight can affect any section of the plant above ground, however it is most noticeable on leaves in the mid to upper canopy. As the tissue dies, infections begin as small, angular, water-soaked spots that turn yellow and finally brown. The spots darken and are surrounded by yellowish-green halos. Spots often merge to form large, dead patches on the leaves.

- **Bacterial Pustule**

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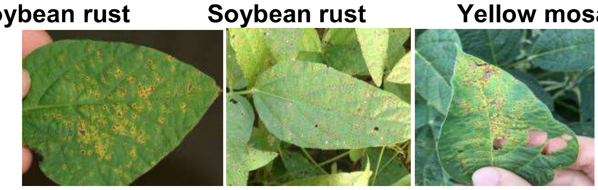
Bacterial pustule is a soybean disease caused by the bacterium Xanthomonas campestris pv. glycines. Despite its prevalence in soybean-producing areas, the disease is of limited consequence because to the high level of resistance seen in most commercial soybean varieties. Snap beans can potentially be infected with bacterial pustule. This pathogen is frequently confused with soybean rust, a far more dangerous disease, since it causes pustules. Bacterial pustules will differ from those of soybean rust, however, because they will not have a natural opening in the pustule, or masses of spores like those of soybean rust. The bacteria overwinter on surface crop residue and on seeds. The bacterial cells are spread during the season by wind-blown rain, rain splashing up from old crop residue, and mechanically during field work when the canopy is wet.

- **Frogeye Leaf Spot of Soybean**

This pathogen is frequently confused with soybean rust, a far more dangerous disease, since it causes pustules. Soybean Leaf Spot (Frogeye) Cercospora sojina is the fungus that causes frogeye leaf spot. The disease is seen in the United States as well as Ontario, Canada. When frogeye leaf spot is widespread in a field, it can result in significant yield loss. The lesions on the leaves are small, irregular to round in shape, grey in color, and have reddish-brown borders. Lesions begin as black, water-soaked spots that vary in size and are most typically found on the upper leaf surface. The central portion of the lesion develops grey to light brown with dark, red-brown borders as it margins. In severe cases, disease can cause premature leaf drop and will spread to stems and pods.

Soybean rust **Soybean rust** **Yellow mosaic**



Bacterial Blight **Bacterial Pustule** **Frogeye leaf spot of soybean**

Above figure shows 1.Soybean rust 2.Soybean rust 3.Yellow mosaic 4.Bacterial Blight 5.Bacterial Pustule 6. Frogeye leaf spot of soybean

Soybean Pod

Soybean (Glycines max), often known as soja bean or soya bean, is an edible seed from an annual legume in the pea family (Fabaceae). The soybean is the world's most economically important bean, providing vegetable protein to millions of people as well as ingredients for hundreds of chemical goods. The soybean plant's origins are uncertain, however many botanists believe it was domesticated in central China as early as 7000 BCE. For thousands of years, the soybean has been utilized as a food and a component of medicines in China, Japan, and Korea.

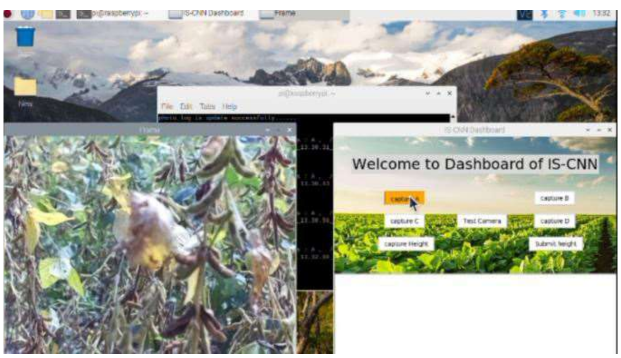
Soybean Flower

Flower of the Soybean In a typical soybean plant, the reproductive phase begins after six to ten trifoliate leaves have formed. Each stalk node generates 3 to 15 flower buds. Soybeans are classified into two categories based on how they blossom. Indeterminate varieties continue to grow upward at the stem's tip for several weeks after flowering begins lower on the stem. The upper nodes will not flower until later in the season. Indeterminate types make up the majority of commercial cultivars. They tend to grow higher and thrive in shorter growing seasons.

III. METHODS

Dataset Description

We gathered real world data for soybean pod and soybean leaf from ICAR (Indian Institute - Soybean Research) and through web scraping, for the evaluation to detect soybean leaf diseases, soybean pod, soybean flower, so that improvement can be made before any lasting harm occurs. The data collected is uploaded to the server i.e. CPANEL after uploading it to server we have process it by using multiple pre-processing techniques, after preprocessing we have performed object detection on the data to detect the object and classified the leaf with the help of neural network and detect the type of disease present on the leaf. Pod and flower of soybean are detected with custom object detection. We have implemented two models i.e. convolution neural network (CNN) for leaf disease detection and custom object detection for pod and flower detection in soybean. For leaf detection the dataset contains total 1822 images form that 1526 images are using as training set and 296 images for testing purpose. For soybean pod total data is 140 from which 100 images are for training and 40 images for testing. For soybean flower total data is 280 from which 200 images are for training and 80 images for testing. We train CNN for soybean leaf detection (multiclass). The model is trained on a TITAN RTX 24G GPU using Keras with Tensor Flow as a deep learning framework. The architectures were optimized using the Adam algorithm, with the categorical cross-entropy function as the loss function. All of the layers were activated with ReLU activation functions, with the exception of the last dense layer, which was activated with Softmax (multiple illnesses) activation functions. We used a 32-person minimum batch size and a 0.001 learning rate.. We have collected data from real world by using sensors, after collecting the data it. The data collected from sensors are through GUI created using Tkinter.



By clicking on capture button we can collect the data captured by camera and upload to the server i.e. CPANEL.

1. Image Pre-processing and Labeling.

Pre-processing on the raw data before it is input to the machine learning or deep learning algorithm are referred to as preprocessing. For example, training a convolution neural network on raw photos will almost certainly result in poor classification results. Preprocessing is also necessary to expedite training.

Techniques for pre-processing:

- **Scaling**
- **Labeling**

One of the most important phases in the pre-processing of data prior to developing a machine learning model is feature scaling. Scaling can make the difference between a bad and a good machine learning model.

Normalization and Standardization are the most frequent feature scaling approaches. When we wish to limit our data to a range between two numbers, such as [0,1] or [-1,1], we implement standardization. Standardization reduces the size of our data unit by transforming it to have a zero mean and a one variance. Refer to the diagram below to see how data looks after being scaled in the X-Y plane.

The task of detecting and marking data with labels, most typically in the form of photos, videos, audio, and text elements, is known as data labeling. In order to manually curate, the procedure often requires human-powered work and, in certain situations, computer-assisted assistance. A machine learning engineer chooses the types of labels to provide information to a machine learning model about what is shown in order to teach the model from these examples. Data labeling aids machine learning engineers in focusing on critical elements that influence their model's overall precision and accuracy.

2. Augmentation Process

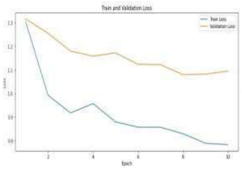
The primary goal of augmentation is to expand the dataset and impart some distortion to the images, which aids in reducing over fitting during the training stage. Over fitting occurs in machine learning and statistics when a statistical model describes random noise or mistake rather than the underlying relationship. Affine transformation, perspective transformation, and basic picture rotations were among the transformation techniques used in the image augmentation. To find a transformation matrix, three points from the original image, as well as their corresponding locations in the output image, were required. Perspective transformation necessitated the use of a 3x3 transformation matrix. Even after the transition, straight lines would stay straight. Simple picture rotations, as well as rotations on the background, were used in the augmentation process.

3. Neural Network Training

The model is trained on a large dataset. The early detection and identification of plant diseases utilizing deep learning methods has as of late gained enormous headway. Identification using conventional methodologies intensely relies upon certain variables, for example, picture improvement, the division of infection locales, also, highlight extraction. Our methodology depends on the identification of infections utilizing a deep learning-based move learning approach. Rather than utilizing standard convolution, we utilized depth wise divisible convolution, which decreased the quantity of boundaries by a huge room for error. We utilize effective model for custom item recognition (soybean pod) and CNN for soybean leaf location; the two has higher precision and requires less preparing time than the first engineering does, as the pre-owned boundaries are many less. We likewise executed custom object detection for soybean pod and flower, which thinks about depth, width, and resolution during convolution. Although the convolution-neural-network-based deep learning design accomplished high achievement rates in the discovery of plant diseases, it has a few limits, and there is a degree for future works. As mentioned, during the training stage, the dataset was divided into two sets, 80% for the training, and 20% for testing. Using Keras and Tensor Flow's deep learning library, the suggested CNN and Efficient Net models were imported into the Python programming language. To enlarge the datasets and overcome over fitting some simple and efficient technique was implemented such as data augmentation and Drop out. These algorithms are trained with a batch size of 32 for 30 epochs with learning rate of 0.001.After training the model it is deployed on web GUI i.e. flask.

IV. RESULTS

The paper presents deep convolution neural networks. The results reveal that we were able to distinguish the leaf spot illness and forecast the proper class utilizing the segmented spot diseases using Deep CNN. Furthermore, it is preferable to utilize DCNN to examine the data collected without extracting any features for the input photos, because these convolutional layers have the ability to detect significant and non-important features for the input images. The model is trained on a large dataset. The early detection and identification of plant diseases utilizing deep learning methods has as of late gained enormous headway. Identification using conventional methodologies intensely relies upon certain variables, for example, picture improvement, the division of infection locales, also, highlight extraction. After implementing Identification of Soybean crop detection using Neural Network The efficiency of the system is evaluated on the basis of these images.



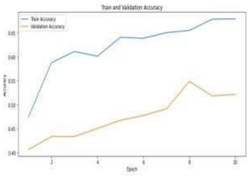


Fig 1: Validation loss and Training loss Fig 2: Validation Accuracy and Training accuracy

The classification report and confusion matrix of our model is given below:

	precision	recall	f1-score	support
0	1.000000	0.987179	0.993548	78
1	0.745763	0.814815	0.778761	54
2	0.916667	0.628571	0.745763	35
3	0.829787	0.735849	0.780000	53
4	0.636364	1.000000	0.777778	28
5	0.886364	0.829787	0.857143	47
accuracy	0.844068	0.844068	0.844068	0
macro avg	0.835824	0.832700	0.822165	295
weighted avg	0.860375	0.844068	0.844254	295

Fig 3: Classification report of the CNN model

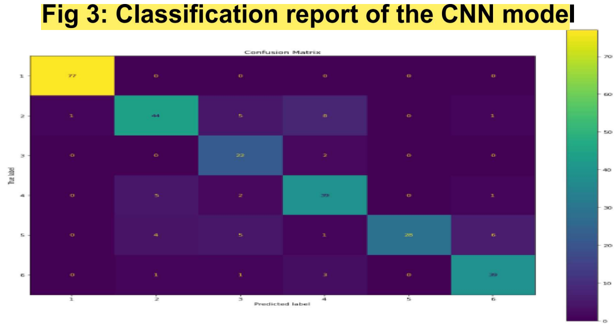


Fig 4: Confusion matrix of CNN

Through Custom object detection the accuracy of pod and flower detection is 0.96% and 1.00% respectively.

Fig 5: Pod detection through custom object detection

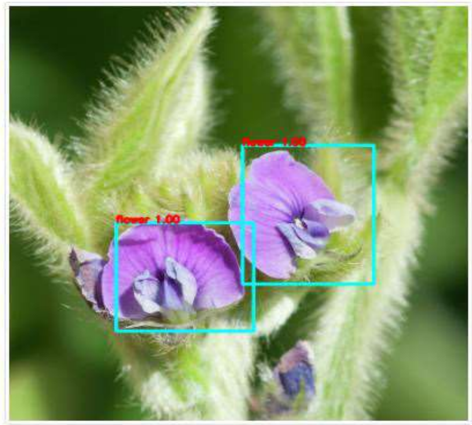


Fig 6: Flower detection through custom object detection

V. CONCLUSION

Because of the severe symptoms and lack of therapies, soybean fungal diseases such as Blight, Frogeye leaf spot, and Brown Spot pose a substantial danger to soybean plants. Traditional diagnosis of the diseases relies on disease symptom identification based on naked eye observation by pathologist, which can lead to a high rate of false-recognition. This work present a novel system, utilizing multiclass deep CNN for detection and classification of soybean diseases using color images of diseased leaf samples. A digital camera was used to capture images of healthy and sick leaves damaged by Blight, Frogeye leaf spot, and Brown Spot. Image enhancement techniques are used to preprocess the captured images. The background of each image was removed by a thresholding method and the Region of Interest (ROI) is obtained. There are many created techniques in the recognition and arrangement of plant diseases utilizing infected leaves of plants. Nonetheless, there is still no productive and compelling business arrangement that can be utilized to recognize the diseases In our work, we used different DL models (Convolution neural network, EfficientNetB0) for the detection of plant diseases using healthy- and diseased- soybean leaf images and soybean pod. To train and test the model, we collected the data from ICAR (Indian Institute - Soybean Research) the standard dataset with 200 images, which were all soybean pod and 1951 images of healthy- and diseased-leaf images of 14 different species. We obtained he best accuracy rate of 99.56 percent in the EfficientNetB0 model after partitioning the dataset into 80 20 (80 percent whole data for training, 20 percent whole images for testing). On colored images, the CNN and EfficientNetB0 architectures used less time to train the images, taking 565 and 545 seconds per epoch, respectively. In comparison with other deep-learning approaches, the implemented deep-learning model has better predictive ability in terms of both accuracy and loss.

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