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IDENTIFICATION OF TOMATO LEAF DISEASE PREDICTION USING CNN

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ABSTRACT

In India tomatoes are broadly vegetable crop. However, the tropical environment is ideal for tomato plant growth, specific climatic conditions and other factors influence tomato plant growth. Aside from these environmental factors and natural disasters, plant disease is a serious agricultural production issue that causes economic loss. As an outcome, early illness detection may produce better results than existing detection methods. As a result, deep learning approaches based on computer vision might be used to detect diseases early. The disease categorization and detection strategies used to identify tomato leaf diseases are thoroughly examined in this study. This study also discusses the benefits and drawbacks of the approaches presented. After all, using a hybrid deep-learning architecture, this study provides an early disease detection method for tomato leaf disease.

Keywords: Artificial Intelligence, Convolutional Neural Network (CNN), Deep Learning, Leaf Disease, Tomato Leaf, Multiclass Classification

1. INTRODUCTION

Agriculture is far more than a manner to feed the world's expanding population. Plant diseases have also wreaked havoc on agricultural and forestry businesses. As just a result, early detection and identification of plant diseases is critical for prompt action. Various techniques can be used to detect plant disease. Definite diseases, on the other hand, are difficult to recognize early on.

Smart agriculture is the following step in agricultural evolution. Precision agriculture, which combines science and technology, has the potential to increase agricultural output. Precision farming also implies lessening pesticides and illnesses by precisely calculating the amount of pesticide required. Precision farming has enhanced so many agricultural sectors as it moves away from traditional methods and toward new approaches. Precision farming's sole goal is to collect real-time data in order to increase agricultural yield and crop quality Arjun (2013),Ferguson et al. (2007).

As a result, they'll have to wait a bit longer to find out what's going on. Under these conditions, advanced analysis, often performed with strong microscopes, is required. Furthermore, diseases devastate a plant's health status, slowing its growth.

Unfortunately, a slew of tomato illness is causing havoc on the crop's leaves. The primary goal of the proposed study is to create a problem-solving solution for recognizing tomato leaf disease using the simplest technique possible while utilizing the fewest computer resources necessary to produce results comparable to state-of-the-art alternatives. Furthermore, automatic feature extraction is used to aid in the classification of input pictures into sickness classifications. As a result, the proposed system had an average correctness of 94%-95%, showing the artificial neural approach's viability even in difficult scenarios Abdul Hakkim et al. (2016).

Precision agriculture employs sensing devices and remote sensing, charting, and inspecting, greater navigation systems, variable rates, the global satellite navigation system, automated steering systems mapping, computer-based applications, and other technologies Chen et al. (1997), Adamchuk et al. (2004).

Smart farming principles focused on infrared variation analysis and treatment, on the other hand, are cutting-edge technologies. To recognise and analyse messes in tomato leaves, this study employs a much more modest adaptation of the convolutional neural organization model. In many other cases, the signals can only be identified in areas of the electromagnetic spectrum that are not visible Ferguson et al. (2007). The goal of this study is to create a simple method that will help farmers identify tomato plant problems without needing to consult an expert. We begin by obtaining an image from the Kaggle dataset and extracting characteristics from it. The attributes are then removed using image conversion and scaling. Finally, the CNN model will be used to diagnose diseases.

- **Image Processing in Precision Agriculture:** Precision agriculture employs deep learning techniques, and its crop protection strategy effectively boosts crop development. Image analysis can be used to correctly identify the item by detecting the sick leaf and measuring and locating the damaged area's border. The purpose of this research is to create a better deep learning system for determining the state of a tomato crop based on a photo of its leaves. We are all aware that the human mind recognizes images much faster than a computer. However, with the introduction of Machine Learning, the era has changed. Deep convolutional neural network models, which can outperform humans in several domains, can ensure superior efficiency on image recognition and classification. Researchers have made advances in visual recognition by guaranteeing their task against Image Net Njoroge et al. (2002).

2. SYMPTOMS OF TOMATO LEAF DISEASE

In their literature review, they examined various segmentation and feature extraction algorithms that could be used to diagnose plant illnesses using images of their leaves. Manual process detecting plant illnesses is extremely difficult due to time constraints, a lack of comprehension of plant diseases, and labor Khirade and Patil (2015).

Traditional methods were inefficient and incorrect. Image processing has been included as a result of several studies for reliable disease diagnosis using plant leaves. Examine various spots and designs on plant leaves to detect the disease. The implementation of digital image processing for more accurate results was a significant step forward. However, after consulting a number of reputable IEEE, international conferences, and international journal publications in this field, it was discovered that none of them provide a cure for the plant ailment Patil et al. (2017).

A practical implementation of processing digital images in agricultural production for recognizing and classifying Brown Spot and frog eye was presented. They use digital image analysis to obtain the form feature representation, which is then used with a K-NN classifier to classify diseases Shrivastava and Hooda (2014).

As a result of the illness, the plant's color, shape, and function may change. We'll go over the signs and symptoms of these ailments, as well as what to look for if your plant's growth appears to be slow. Leaf disease classification and diagnosis are crucial in reducing agricultural losses. Various plant leaves transmit different diseases and exhibit different symptoms.

- **Leaf Bacteria Spot:** Bacterial leaf spot is triggered by four Xanthomonas species. It infects all tomato varieties and, in the Midwest, causes medium to severe harm to tomato fruit, rendering it unmarketable because of quality issues. Symptoms include yellowing leaf lesions and huge crusty spots on the fruit.
- **Leaf Mold:** Tomato production under large tunnel and plastic has increased dramatically in recent years, in part due to customer demand for "local" foods. While growing under certain conditions may aid in the prevention of certain illnesses, it can also hasten the spread of others. Tomato leaf mould disease is one of the most common. It is caused by the fungus Cladosporium fulvum, which has recently been renamed 'Fulvia fulva' by seed manufacturers and dealers and 'Passalora fulva' by mycologists. The disease is rarely found on field-grown plants, and when it is, it is caused by infected greenhouse-grown transplants.
- **Spider Mites Two-Spotted Spider Mite:** The two-spotted spider mite is the most common mite species in New England that attacks vegetable and fruit crops. Spider mites have been found in plants such as tomatoes, vine crops, eggplants, potatoes, melons, cucumbers, and others. Two-spotted spider mites are one of the most common eggplant pests.
- **Target Spot:** Target spot on tomato plant is difficult to identify in the early stages because the illness replicates several other fungal tomato diseases. When diseased tomatoes ripen and turn red, the fruit develops circular spots with concentric, target-like rings and a velvety- black fungal lesion in the center. As the tomato matures, the "targets" become pitted and larger.
- **Yellow Leaf Curl Virus:** A DNA virus of the Geminiviridae family and the genus Begomovirus, also known as 'Tomato Yellow Leaf Curl Virus.' TYLCV is the most destructive tomato disease, and it may be widespread in tropical and subtropical regions, causing significant economic losses.
- **Tomato Mosaic Virus:** Tomato mosaic virus symptoms can appear at any stage of growth, and the plant can be infected in all parts. They are frequently seen on foliage as a general mottling or mosaic appearance. When the plant is severely damaged, the leaves may resemble ferns with raised dark green regions. Leaves may become stunted as well.

- **Leaf Spot on Septoria:** The Septoria leaf spot is one of the most well-known tomato plant leaf diseases. The first sign of this fungus' presence is a tiny, round patch with a greyish-white center and black borders. Tiny black specks may appear in the center. When exposed to hot, humid conditions for an extended period of time, the leaves of sensitive tomato plants turn yellow, wither, and fall off.
- **Early Blight (Alternaria):** Alternaria is a parasite that induces tomato leaf spots and an early blight. On the lower leaves, brown or dark areas with dim edges appear, similar to an objective. Natural product stem closes are extremely sensitive, resulting in major, profound dark blotches with overlapping circles. This tomato plant disease is caused by a fungus and just seems after the plants have obtained fruit.
- **Blight in the Late Stages:** The fungus Phytophthora infestans caused a tomato plant disease called Late blight, which appears in perfect, wet weather after the growth season. Frost damage appears on plants as uneven green-black splotches.

Fruits with large, irregularly shaped black areas can be destroyed quickly. This fungus, which causes tomato plant disease, also affects potatoes, and can be spread by them. The same precautions as with Septoria leaf spot should be taken. Figure 1

Figure 1

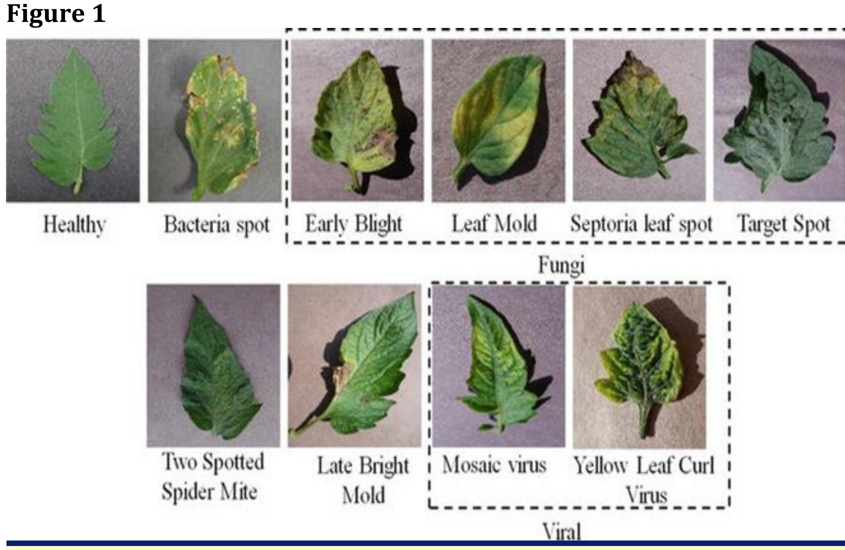


Figure 1 Tomato Healthy and Types of Disease

3. RELATED WORKS

In this paper, a Dense Layer with residual convolution layers modulus is used for classification. Experiments show that on the tomato dataset, RRDN can achieve a satisfactory performance of up to 95% Zhou (2021).

Our findings indicate that our method can improve detection performance on tomato leaf disease datasets. It is rooted on a residual dense network detection of leaf diseases model and is inspired by RDN in picture high - resolution tasks. With the help of an architectural model adjustment, we created a classification model that outperformed advanced models in terms of accuracy.

We will try to comprehend the transport of Tomato dataset via model fit to other plants although this model is appropriate for a tomato set of data. Enhance your ability to generalize. We hope to apply this work in the future to make a small contribution to the development of agricultural intelligence.

- **Machine Learning:** A type of machine learning is artificial intelligence. A system is trained from its previous experiences and improves without being coded. Instead, it focuses on creating a computer program that allows the data accessed to be used for self-learning.
- **Deep Learning:** A portion of machine learning that excels at finding patterns in massive amounts of data is deep learning. Detecting objects in images, for example, is accomplished through the use of three or more layers of artificial neural networks each of which extracts a huge number of visual properties.
- **Neural Network:** A feed-forward back-propagation Neural Network-based approach to identifying and categorizing illnesses in grape leaves was developed. The author used pictures of a grape leaf with a complicated backdrop to make the diagnosis. Anisotropic diffusion is then used to remove noise from the image before it is segmented using k-means clustering. Eventually, neural networks are utilized to analyze the results. The results were tested on downy mildew and powdery mildew matrices, and the author claims to have an accuracy of about 100% when using the color characteristic alone Sannakki et al. (2013).

  A computer model functions in the same way that neurons as in human brain do. Each neuron receives input, acts upon this, and then transmits the results to the preceding neuron.
- **Deep Convolutional Neural Network:** The feature recognition system employs the leaf recognition method. Plant leaves are identified using the Convolutional Neural Network (CNN). Before incorporating properties into CNN, PCA obtains and improves them. The neural network was based on the biological nervous system as a pattern recognition paradigm. It is made up of many neurons, which are densely paired processing components that produce a sequence of factual activations Cheng and Malhi (2017), Lee et al. (2018), Aarthi and Harini (2018).

For example, when given input, early neurons are activated, and weighted connections from previously active neurons activate other neurons. Depending on how neurons are employed and coupled, large causal chains and links between computational stages may be required. Deep neural networks (DNNs) are neural networks with a large number of hidden layers.

As a result of its growth, Deep Learning has made significant progress in image classification. Deep learning algorithms aim to learn the feature hierarchy automatically. At different degrees of deliberation, this self-learned component permits the framework to dissect complex contributions to yield planning capacities straightforwardly from getting to information without depending on human-made highlights Jadhav (2019), Mhatre and Lanke (2021), Song et al. (2020). We developed "IDENTIFICATION of tomato leaf disease using CNN" using Deep learning. We just took a step and started to collect lots of images of crop leaves. We require space capability to get the correct information.

Then, at that point, we pick which calculation is ideal for tackling this issue, and we choose "Convolution Neural Network" not surprisingly (CNN). Be that as it may, we gain less precision utilizing move learning engineering, which admirably prepares and tests datasets Wu et al. (2019), Barbedo et al. (2018). Pre-processing & feature extraction, we select leaf data such as color, shape, and texture are helpful in pattern recognition, classification. It gives us more than 81% accuracy on training and validation data set in just 20 epochs. After that, we deployed this model on the flask. Figure 2

Figure 2

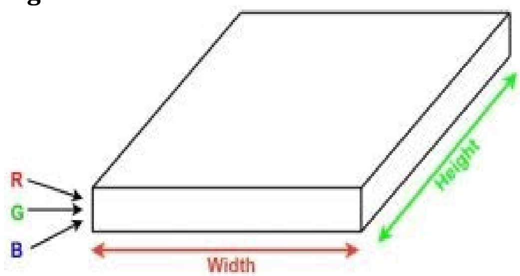


Figure 2 Convolutional Neural Network

Convolutional neural networks, often known as covnets, are neural networks with shared parameters. For example, assume you have a picture. It may be seen as a cuboid with length, breadth (image size), and height (as images generally have red, green, and blue channels) Sun et al. (2019).

Imagine taking a tiny section of this image and running a little neural network on it, say with k outputs, and representing the results vertically. Slide the neural network across the entire image, and we will obtain a new image with changing width, height, and depth.

We now have more channels than simply R, G, and B, but they are smaller in width and height. Convolution is the name for this procedure. It will be a standard neural network if the patch size is the same as the picture size. We have fewer weights because of this tiny region Hana et al. (2017).

- **How CNN Works:** A Convolution is one of the Neural Network layers, which also include ReLU Layer, Pooling, Fully Connected, Flatten, and Normalization CNN Hana et al. (2017) would be used to compare the photographs piece by piece.

  The item is known as a feature or filter. CNN uses the weight matrix to extract specific characteristics from an input image while preserving details about just the image's spatial configuration. CNN follows the following layers:

- **Convolutional Layer:** It This layer resonates the feature and the image before multiplying the pixel in an image by the feature pixel. After completing the associated matrix multiplication, CNN adds and divides the result by the total number of pixels, generates a map, and stores the filter's value in it.

  After that, the feature is moved to every other location in the image, and the matrix output is generated. The procedure is then repeated for the remaining filters. As a result, this layer adjusts the filter just on image in every possible location.

- **ReLU Layer:** ReLU The acronym ReLU stands for Rectified Linear Unit. In this layer, every negative value in the filter images will be removed and replaced with zeros. When the input and output are both zero, the function activates a node. If the information grows, the dependent variable has a linear relationship. As a result, it strengthens the neural network by increasing the amount of training.

- **Pooling Layer:** This layer shrinks the image by extracting the highest value from the filtered image and transforming it to a matrix. It also prevents overfitting.
- **All Fully Connected:** This is CNN's final layer, and it is here that the absolute categorization occurs. First, a single list containing all of the purified and compressed photos is created. Figure 3

Figure 3

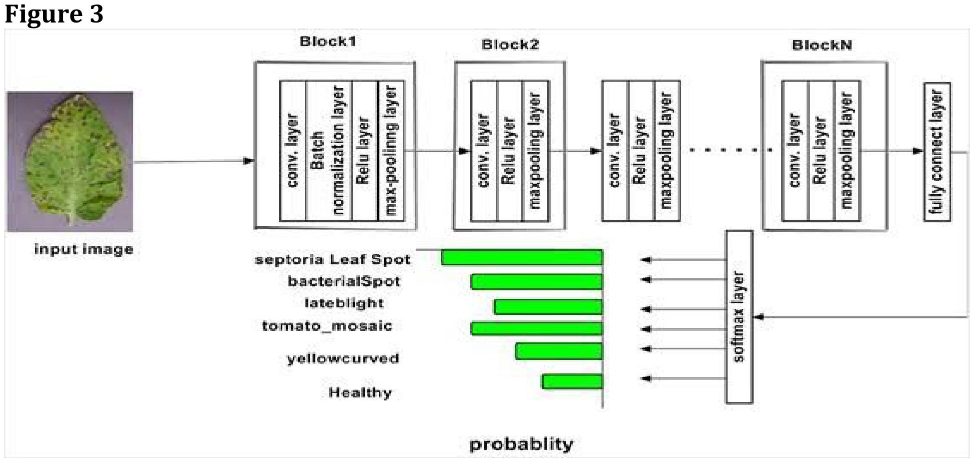


Figure 3 CNN Works With Different Layers

4. EXPERIMENT

4.1. DATA DESCRIPTION

The dataset was constructed using a tomato plant leaf image, as well as healthy and unwell photos with multiple categories Cotton Disease Dataset. (2020b).

For the analysis of the leaf health identification task, we use the Kaggle dataset.

The dataset is divided into two parts: 21,416 total images, 18345 total testing images, and 18345 total training images. The data is divided in an 80/20 ratio, with 80% for training and 20% for testing samples used to train the deep neural network.

The dataset enables machine learning researchers with new ideas to jump right into an important technology area without having to gather or generate new data sets, allowing for a comparing result to the efficiency of previous work. The Leaf image is used to collect data, which includes healthy and unhealthy individuals of various classes. The data set is divided into two sections: one large group is used for deep neural network training, as well as another snippet is used to evaluate the model. Finally, a set called the test set is used. All models and training are done with Keras and TensorFlow as a deep learning library, on high-end GPUs like the T4 and P100, as well as TPUs.

For all architectures, the Adam optimizer was used, and indeed the loss function was the declarative cross-entropy function. Except for the final dense layer, we also used ReLU activation functions in all layers.

4.2. METHOD OF EVALUATION

In In terms of agriculture conserving, our farmers must check the leaves and disease of the plants by taking a sample or checking on the field. Because of the shortage of data and numerous other variables, there is a chance of error. So we ought to automate this so that farmers can quickly build their creation.

In this paper, we built a DCNN from the ground up: Deep learning improved the learning capacity of features in highly dimensional unprocessed data, deep learning algorithms in images and audio segment extraction, and supervised learning in general.

As a result, as a viable candidate for classification task modulation, an integrated understanding of deep Learning algorithms solves the central problem of sample selection and extraction. As a result, it demonstrates the mixture of simple functions in more effective and complex features to achieve a more efficient and complicated classification.

Furthermore, deep neural networks have a multilayer structure that allows them to better extract signal properties by avoiding the time-consuming manual selection of data properties. In this project, we build a small-scale deep convolutional neural network (DCNN), evaluate its performance, and then build a more advanced deep learning network using art data and techniques. Figure 4

Figure 4

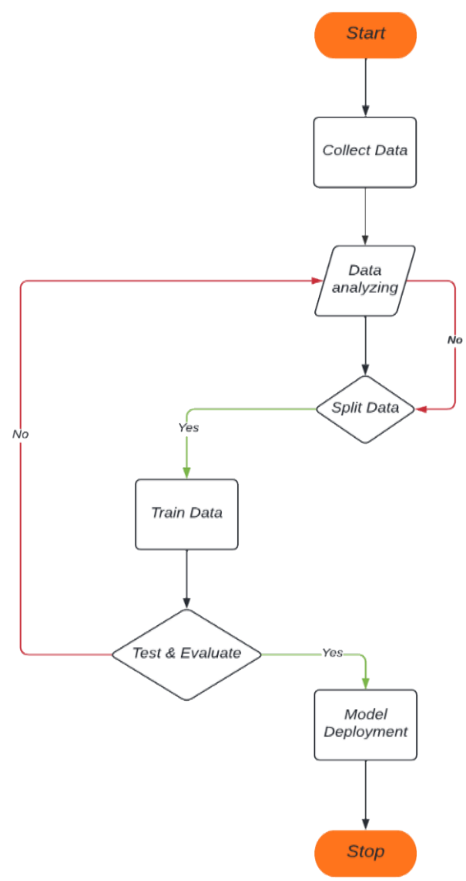


Figure 4 Methodology Flowchart

In this paper, we built a DCNN from the ground up:

1) Splitting the dataset into two parts, namely the training dataset (1951 leaf img) and the validation dataset (400 leaf img).
2) Our DCNN model has one input layer, multiple conv2D layers, two dense layers, and a few dropout layers in between.
3) The DCNN model is trained on the training and validation datasets.

4) Following training, the test set's true-positive, false-positive, accurate-negative, and false- negative values were recorded sequentially.

   Figure 5, Figure 6

Figure 5

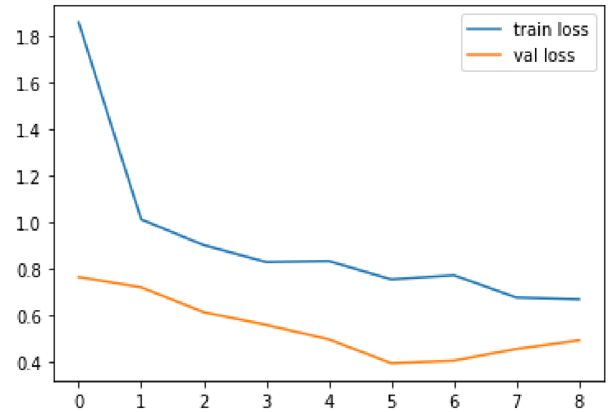


Figure 5 Training vs Validation Loss of CNN Model

Figure 6

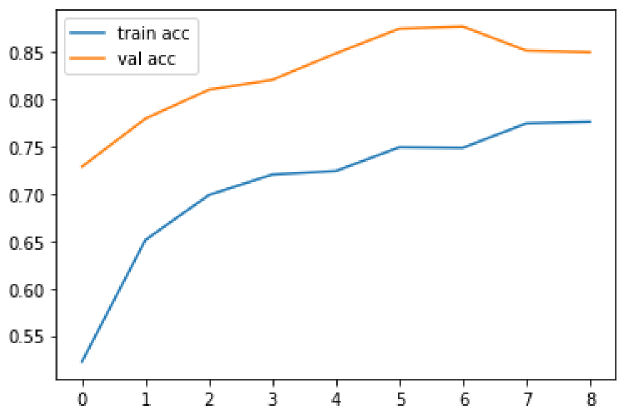


Figure 6 Training vs Validation loss of DCNN Model

4.3. RESULT ANALYSIS AND DISCUSSION

Our job was to train a deep convolutional neural network (CNN) to recognize and analyse leaf images. We used the Kaggle Lead Disease Dataset, which we chose in two main categories [Diseased Leaf, Fresh Leaf], a dataset comprising leaf images in the format of arrays from these two categories. Each category's leaf is accessible in a variety of leaf pictures from various angles.

DL techniques continue to show great promise in terms of improving identification sensitivity and accuracy, especially for short-term data. DCNN, while on the other hand,

can automatically extract features, saving both time and effort. Once the model has been tested on the test dataset, the results are reported. The overall accuracy of the model is 96.6%.

We reassign all the weighted data to your model so the model can run and reassign error then call the epoch of the model which is consistently running with data and trying to increase accuracy and decrease data loss.

The accuracy result of our deep learning model clearly shows that there is an increment inaccuracy as the model epoch grows. The accuracy outcome of our deep learning model clearly shows that as the model epoch increases, so does the inaccuracy. The model loss result clearly indicates that as the model epoch is increased, Loss decreases. Figure 7

	Precision	Recall	F1-Score	Support
Tomato_Bacterial_Spot	0.96	0.89	0.92	100
Tomato _Early Blight	0.77	0.77	0.77	100
Tomato _Late Blight	0.78	0.93	0.85	100
Tomato_Septoria_Leaf_Spot	0.90	0.82	0.86	100
Tomato Spider Mites Two- Spotted_Spider_Mite	0.77	0.81	0.79	100
Tomato Target_Spot	0.98	0.82	0.89	100
Tomato Tomato_Yellow_Leaf_Curl_Virus	0.84	0.81	0.83	100
Tomato Tomato_Mosaic_Virus	0.90	0.98	0.94	100
Tomato Healthy	0.89	1.00	0.94	100
			0.93	
Accuracy	0.98	0.89	0.87	1000
Macro Avg	0.88	0.87	0.87	1000
Weighted Avg	0.88	0.87	0.87	1000

Figure 7

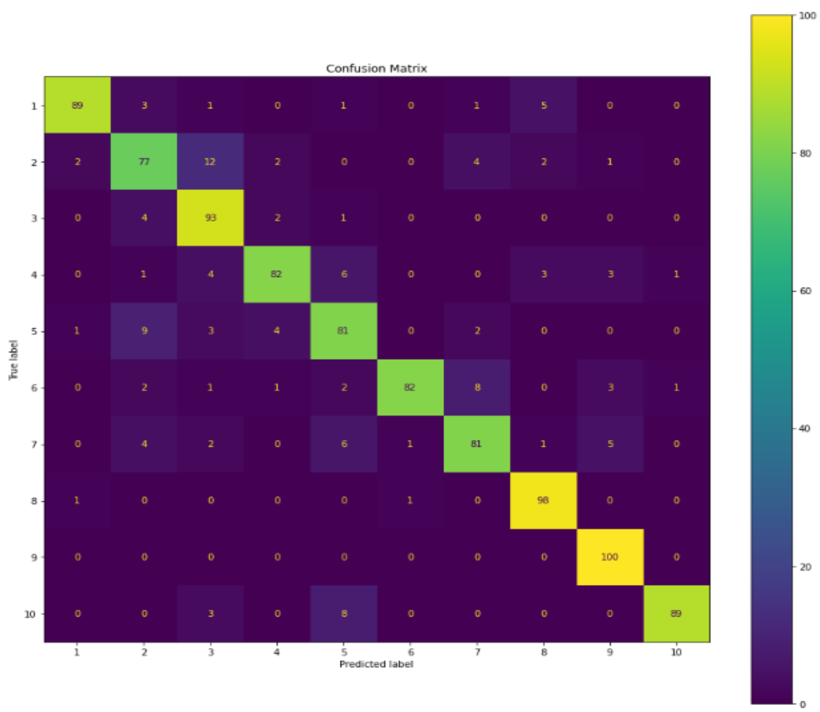
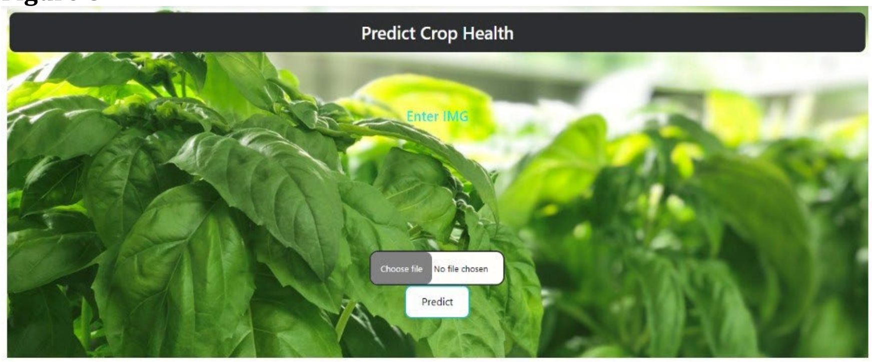


Figure 7 True Label vs Predicted Label

After implementing the Deep learning-based leaf classification system, the system is evaluated as follows: Figure 8, Figure 9, Figure 10

Figure 8



Flask UI

Figure 8 Flask Framework

Figure 9

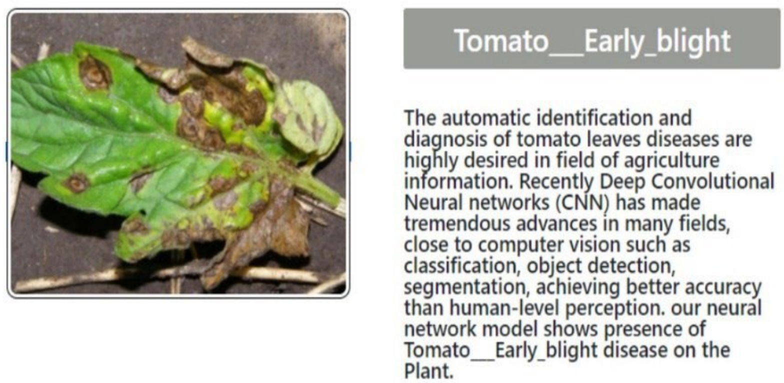
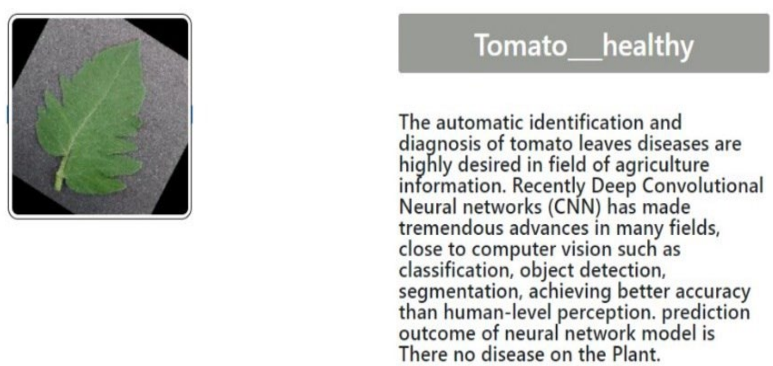


Figure 9 Predicted Leaf Disease

Figure 10



Healthy Leaf Result

Figure 10 Predicted Healthy Leaf

5. CONCLUSION

We By launching our model on a flask that observes illness and infected leaves, we project the classification through our system. In leaf detection, the project has several verticals. So far, we have been successful in locating the diseased leaf. In the future, we will separate the illness based on whether it is caused by microorganisms, fungi, or infectious agents and provide the farmer with a solution in the field. The project is concerned with identifying the diseased leaf. The Convolutional Neural Network Algorithm is used to accomplish this. If the disease affects the leaf, the information is transmitted through the system. This assists the farmer in locating unhealthy leaves for the field.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

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