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# Fungal Infection on Tomatoes Using Image Processing With Deep Learning Techniques

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***ABSTRACT***
*Historically, the severity of leaf symptoms was the most important diagnostic indicator for plant diseases. As the day progressed, the amount of plants to be cultivated grew, and so did the level of complexity. Due to diverted manure practises, modern illnesses are substantially different from historical diseases, making diagnosis difficult for even seasoned farmers and agronomists. Although there is no such thing as a "wrong" diagnosis or a "one-size-fits-all" therapy, there is nothing to lose by seeking treatment after a diagnosis has been made. Due to the extensive incidence of vascular fungal infections and the harm they bring to plants, this issue impacts a wide range of crops. Fusarium wilt is a fungus that may infect a broad range of plant species (FW). This soil-borne fungal disease affects tomatoes, sweet potatoes, tobacco plants, legumes, and cucurbit plants. The primary objective of this research is to facilitate the identification of FO disease in tomato plant leaf. In addition to enhancing precision, the new strategy doubles the number of times sickness categorization and identification are conducted during model development. 60 percent of the 87k images in the public database depict leaves that have been damaged in some manner, whereas 40 percent depict leaves in excellent condition. Our suggested hybrid method correctly identified the condition in a massive dataset (96 percent).*
***Keywords:*** *Plant diseases, Fusarium Oxysporum, Machine learning*

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## INTRODUCTION

Food safety measurement on a worldwide scale is challenged by a variety of variables; including plant diseases.[1] Small holder farmers are mostly responsible for agricultural output in many third-world nations. According to the 2013 annual report of the United Nations Environment Program (UNEP), losses due to pests and diseases and monsoon change management practises exceeded fifty percent. Historically, plant diseases were assessed by examining the leaves and estimating the severity of the symptoms [1]. Due of the vast quantity of plants being farmed, daytime complexity increased. Due to the practise of diverting manure, even the most experienced farmer or agronomist may find it difficult to recognise current illnesses [2, 3]. However, once a diagnosis has been made, there is neither a definitive cure nor a therapy that should be avoided. As seen in Figure 1, when tomato plants are subjected to FO disease, their leaves wilt.

**Figure 1:** *Fusarium Oxysporum* disease in tomato plant leaves.

Food safety measurement on a worldwide scale is challenged by a multitude of variables; including plant diseases [1]. Individuals who cultivate little parcels of land are responsible for agriculture in many developing nations. According to the 2013 annual report of the United Nations Environment Programme (UNEP), losses attributable to pests, diseases, and monsoon change have exceeded fifty percent. Historically, a plant's health was assessed by examining its leaves to identify the existence and severity of symptoms. Because so many plants were being cultivated, daylong complexity increased [4-6]. Diverted manure may generate a variety of current disease signs, making proper diagnosis difficult for even the most experienced farmer or agronomist. Despite the fact that once a diagnosis has been made, there is neither a guaranteed cure nor an inappropriate therapy to pursue. Figure 1 depicts how the FO disease causes tomato plant leaves to wilt.

**Figure 2:** Effects of *Fusarium Oxysporum* disease in tomato plant.

On this page, we will describe the diseases that are brought on by FO, with a particular focus on how these diseases affect the tomato plant. Recently, several technologies based on image processing and identification have been used to cure illnesses that affect the leaves of tomato plants [7, 8]. Figure 2 presents an assortment of tomato plant leaf kinds, each of which has the potential to contribute to an improvement in the accuracy of the prediction.

## PRELIMINARIES

By examining the plants' leaves and the environment around them, the agronomist can identify and predict the presence of plant diseases. Mohanty and colleagues [9] conceived of and carried out the construction of the automated computing system. It was an early user of simple mobile applications like those that make cutting-edge technology available to the general public. Additionally, it was an early example of the sort of simple mobile applications that make cutting-edge technologies accessible to the general public. LeCun et al. have developed a GPU processor that uses machine learning in order to anticipate diseases that might affect plants. New methods for diagnosing plant diseases were another topic that was covered in this discussion. Deep learning and image recognition, in his view, have a great deal of potential for the detection of two-sector problems. Large-scale voice-recognition datasets are also helpful for accurate task prediction [10]. Carranza-Rojas et al. discussed the methods that may be used to detect plant diseases by using deep learning in their paper [11]. Yang and Guo provide some suggestions for diagnosing the conditions that cause plant sickness. Deep learning is compatible with a cutting-edge new technology called the Convolutional Neural Network, or CNN for short. CNNs are designed to identify diseases in plants. Not only does the deep learning approach perform well with huge datasets, but it also results in higher levels of accuracy [12]. Lee et al. [13] recommend using CNN techniques in order to identify the plant based on pictures of its leaves. Grinblat et al. design a neural network in order to accurately identify plant species based on their leaves [14].

 

**Research gap:-**

Both the predictions of the FO disease in plants and the research activities that emerge from such predictions often include errors. Numerous studies identify the practise of prediction by using the most effective classifier or a combination of classifiers as a possible topic for further research. In order to get the best possible outcomes with our suggested solutions, we have combined image processing with a classifier algorithm. More precise predictions of the FO illness that may be found in plant leaves can be produced.

## MATERIAL AND METHODS

This study makes use of a variety of methodologies, each of which is carried out in sequential order, in order to detect the FO illnesses that may be found in tomato leaf tissue. Real raw photos have a grainy and noisy quality to them. Therefore, in order to get rid of the noise and supply you with clear images, we recommend making use of a hybrid strategy for the preprocessing. The last step involves naming each picture and placing it into the appropriate category [15, 16]. As a consequence of the FO disease, the plant's older leaves and stem will take on a yellow colour that looks sickly. There is a possibility that the roots have also become discoloured. It is conceivable for the fungus to grow and thrive on seeds, but this will only occur after an extremely prolonged period of incubation.

**SUCCESSIVE STAGES**

**VTT phase:**

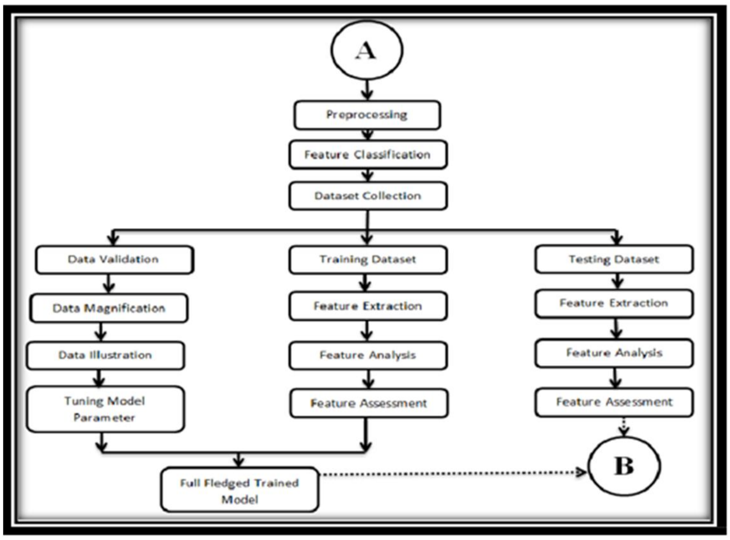


**Figure 3:** VTT Phase at Proposed framework.

Even when the picture recognition approach was used, a great number of inaccurate predictions were generated. In order for our plan to be successful in fixing this issue, it is essential that we make use of the VTT stage. During this phase, we will validate, train, and test data in an effort to achieve a higher level of accuracy in our predictions. As a result, we are going to get started by teaching the machine learning algorithm using pictures of plants in good condition. During the period in which data is being collected, this picture will be utilised to categorize various characteristics [17]. Please refer to Figure 3 for an illustration of the VTT phase of our suggested technique. This section may be divided into three subsections, as follows:

**Data validation:** In situations with complex limits, the process of authenticating data is essential. The system and its procedures were able to successfully complete this complicated computation. An example of this would be magnifying the leaves of a tomato plant in a photograph so that the plant seems to be more spectacular than it really is. The veins on the leaves of a tomato plant become more noticeable when seen at a larger size in an image because the scale has been increased.

**Data illustration:** The process of transforming one set of data into another in order to improve pattern recognition. The various patterns that may be found in enormous datasets are organised into categories that are simple to understand thanks to this data visualisation. As a consequence of this, it has the potential to improve accuracy [18]. In order to acquire the fully trained model, testing data of feature assessment are compared with the validation and training data model. Figure 4 presents the conclusive findings of this approach for the evaluation of features, together with a forecast of the subsequent stage**.**

$$P\left(\frac{A}{t_l}\right) = \frac{P(t_l/A)\,.\,P(A)}{P(t_l)}$$

P(A) = Prior probability of class
$(tl/A)$ = The probability of predictor by given class
$(tl)$ = Prior probability of target predictor (Tomato Leaf)
$P$ ( ) = Posterior Probability of class A given by the predictor

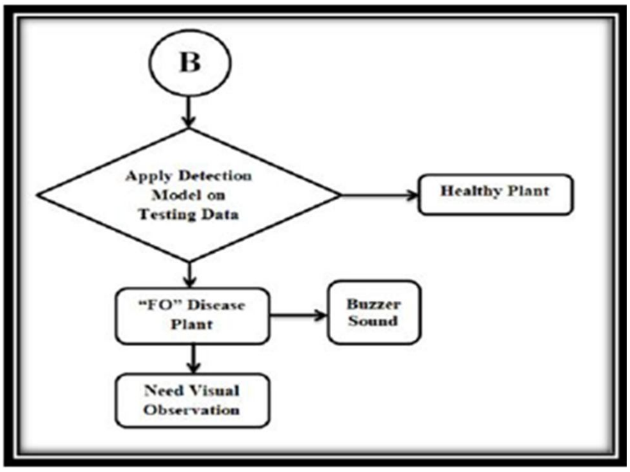


**Figure 4:** Detection model for FO disease in final stage.

**Final Stage Prediction:** When we get to this step in the detection model, all of the potential outcomes have been analysed by the prediction processing units. Using the ML method, we are able to properly label and identify this [19]. To reiterate, there is no need for human testing if it can be shown that the plant is healthy. The need for human intervention arises in the event that an algorithm identifies the FO disease in a tomato leaf. Figure 5 illustrates the framework of the naive Bayes method for analysing data.

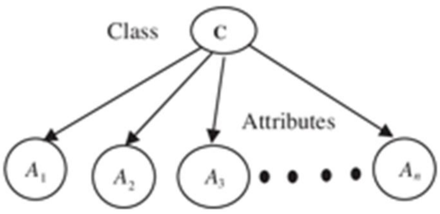


**Figure 5:** Structure of Naïve Bayes approach.

## RESULTS AND DISCUSSION

We provide an innovative approach that blends naive Bayes with an image recognition algorithm in order to get better results. If you check at the first level, you will obtain a rough estimate of how probable it is that your plants will get unwell; if you check at the second level, you will get a prognosis that is much more accurate. As can be seen in Figure 6, this assortment of leaves is put to use in the process of picture recognition. Figure 6 illustrates a variety of leaf states that may be seen on tomatoes.

Tomato Leaves for Classification

**Figure 6:** Image classification for leaf.

After the sick plant has been removed, subsequent tomato plants that are planted in the same location will have greater success. There is some indication that reducing the occurrence of FO disease may be accomplished by using a rotational cropping pattern and/or by making amendments to the soil. Examine the histogram to get a comprehension of the spatial distribution of the image's pixels, as shown by this photograph of a tomato leaf (Figure 6). We investigate the degree of prediction supplied by three FO indicators using a bar chart. The accuracy of today's technologies for processing photos has improved significantly, but these systems also need ever-smaller samples of the original images to be supplied. In addition, the operation of the algorithm makes it impossible to do this within any reasonable amount of time. Because it has been independently confirmed by two different sectors, the procedure that we have suggested has a higher level of dependability. The prediction accuracy calculation that occurs after the 50K image dataset leads the used image processing algorithms to need more time for execution (NA).

## CONCLUSION

Within the scope of this investigation, we suggest a collection of methods that, when combined, provide more accurate outcomes. The use of a method that identifies two factors contributed to the production of more reliable results. Even when using only a single identifying feature in combination with an image recognition or ML approach, there was a reduction in accuracy. The classification method that we devised for the purpose of diagnosing FO illness showed promising results in terms of its ability to accurately predict outcomes. After establishing a model that has great accuracy in real-world conditions, we may be able to give additional assistance for early warning prediction of plant disease.[18] We want to implement several forms of location-finding technologies in a variety of agricultural contexts. Because of this, the time it takes to correctly identify plants that are infected with illnesses will be cut significantly. In the not too distant future, the photographs that were captured by a flying drone within the factory may be classified into a variety of categories. The author is certain that the information presented in this article will be helpful to agronomists and farmers who think ahead of the curve.

## Conflict of Interest

None

## Funding

None

## Ethics Statement

NA

## Informed Consent

NA

## Data Availability

NA

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