# Analysis of Crop Diseases Using IoT and Machine Learning Approaches

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**Abstract.** For agricultural and farming practices to be more productive and cost-effective, it is imperative that the implementation of new technologies such as the Internet of Things (IoT) and Machine Learning be strongly considered in order to improve methods and procedures. In keeping with the evolution of agriculture, disease control measures have also evolved. Now a days, disease in plants can be undoubtedly identified using computers. Climate condition can be assessed for timely diagnosis and precise detection of crop diseases in order to control these diseases at an early stage. In order to prevent plant diseases from attacking, it is imperative that solutions are developed for the early prediction of disease attacks. An existing approach to disease detection uses computer vision, which detects diseases after they have already developed. The objective of this paper is to provide an insight into newly developed Internet of Things (IoT) applications in the agricultural sector, with a focus on sensor data collection and early detection of diseases.

**Keywords:** Plants diseases · Internet of Things · IoT · disease prediction · Support vector machine · Random forest

## 1 Introduction

Cultivating is quite possibly of the most established occupation throughout the entire existence of humankind. Now a days farmers face challenges like never before. With rising global population rates and continuous changes in climate, there is immense pressure on the agricultural industry to produce more food. The production of crop is reducing due to the attack of the disease [1]. Today, there is a pressing need to unravel the issues like utilization of destructive pesticides, controlled water system, control on contamination and impacts of climate in farming practice. There is a possibility that any error during diagnosis could lead to incorrect control and overuse of pesticides. To spray a limited and enough pesticide/fertilizer at a specified target area is one of the big challenges. Detection of diseases at early stage is necessary for good development of plant [2]. With the help of Machine Learning, crop field environmental conditions based on the Internet of Things (IoT) can be accurately predicted to predict the occurrence of plant diseases.


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The paper has been divided into distinct sections. In Sect. 2, we discuss background. Section 3 presents the methodology adopted to survey the research papers. Section 4 describes a discussion and analysis of our findings. Finally, Sect. 5 concludes the research work.

## 2 Background

A plant disease as per plant nutrition testbook is defined as "anything that prevents a plant from performing to its maximum potential". Diseases are anomalous conditions that adversely affect an organism's structure or function. It can cause damage to a plant, animal, or human organism. Any disease has specific symptoms and signs that appear as a result of any disease. Bacterial, Fungal, and Viral are types of diseases. Powdery Mildew, Black Spot, Bacterial Canker, Shot Hole, Black Knot and Rust are common plant diseases. It can affect leaves, fruit, or even the whole plant depending on the severity of the infection. The following is a list of some of the major plant diseases.

### 2.1 Bacterial Plant Disease

Infections caused by microscopic organisms are called bacterial infections. Biological organisms consist of one cell. Table 1 shows some bacterial plant diseases and the name of the plant which get affected with symptoms.

### 2.2 Fungal Plant Disease

A large part of the productivity loss in a plant can also be attributed to fungus. Fungi such as ascomycetes and basidiomycetes primarily cause plant diseases.

Table 2 shows some fungal plant diseases and the name of the plant which get affected with symptoms.

**Table 1.** Bacterial Plant Disease

| Disease Name | Plant affected | Causal Organism | Symptoms |
|---|---|---|---|
| Citrus stubborn disease | Citrus and stone fruits and vegetables | Spiroplasma citri (MLO) | Chlorosis Yellowing of leaves Shortened internodes |
| Soft rot | Many fleshy tissue fruits such as carrot, cabbage, celery onion | Erwinia, carotovora | Soft decay of fleshy tissues that becomes pliable and supple |
| Fire blight | Apple and pear | Erwinia amylovora | Blossoms appear water-soaked |

**Table 2.** Fungal Plant Disease

| Disease Name | Plant affected | Causal Organism | Symptoms |
|---|---|---|---|
| Downy mildew | Grapes, grasses, Vegetables | many species of the family Peronosporaceae | Yellow irregular spots presence is observed on the uppermost epidermal layer, Downy fungal growth appears on the underside |
| Late blight of potato | Potato | The fungal pathogen Phytophthora infestans. | Lower leaves exhibiting dark green to black or purplish lesions with pale green margins, saturated with water. |
| Citrus exocortis | Orange, lemon, lime, and other citrus plants | Citrus exocortis viroid (CEV) | Affected trees present clear vertical fissures in their bark, with thin strips of partially detached bark. |

**Table 3.** Viral Plant Disease

| Disease Name | Plant affected | Causal Organism | Symptoms |
|---|---|---|---|
| Cucumber mosaic | Cucumber, bean, and other plants | Cucumber mosaic virus (CMV) | The mottled appearance of leaves (mosaic pattern) |
| Potato spindle tuber | Potato and tomato | Potato spindle tuber viroid (PSTV) | Spindle-shaped tubers exhibiting stunted growth are present. |
| Tomato spotted Wilt | Tomato, pepper, pineapple, peanut, and many other plants | Tomato spotted wilt virus (TSWV) | The leaves exhibit a necrotic region with concentric rings, the area initially yellow in color and progressing to a red-brown shade. |

## 2.3 Viral Plant Disease

An organism with living cells affects the plant because it is a living organism. Table 3 shows some viral plant diseases and the name of the plant which get affected with symptoms.

In order to take effective control against the disease attack, a solution that predicts disease occurrence is needed to prevent plant damage. It is clear that the environment plays a significant role in disease attack. It is therefore possible to predict crop diseases based on the environmental conditions. A prevention system has been developed to aid

crop field managers in improving management and limiting the spread of fungal diseases [3].

## 3 Methodology

In [4], an IoT monitoring system was developed by the authors specializes in the use of a wireless sensor network to collect environmental and soil information data. A variety of diseases of tomatoes and potatoes have been detected early by using the collected data. In [5], the authors crafted a monitoring and prediction system for the forecasting of mildew infestation in a vineyard. To generate efficient prediction models, machine learning algorithms can be used instead of traditional methods since they are more effective in detecting diseases. In [6], the utilization of a Hidden Markov Model has been proposed as a means to enable the early detection of diseases in grape crops through the establishment of a rigorous monitoring system.Hidden Markov Models assess a number of environmental factors, including temperature, humidity, leaf condition, etc., to predict grape plant diseases. A server was accessed by Zig-Bee for the purpose of transferring the data (standard designed for low-power wireless data transmission). Providing favorable conditions for those responsible for spread of grapevine diseases was the National Center for Research on Grapevines' (NCRG) role in the classification process. In [7], a Naive Bayes Kernel Model was employed to predict illness based on environmental and soil data acquired through an Internet of Things (IoT) tracking system. A KNN (K Nearest Neighbors) model was implemented to facilitate the early detection and timely identification of agricultural diseases [8]. The prediction was based on the extraction of multiple parameters from the field, such as atmospheric temperature, atmospheric humidity, $CO_2$ concentration, soil moisture, soil temperature and leaf wetness. The results of the environmental data confirmed the accuracy of the model, thus verifying the effectiveness of its use in the early detection of disease. Similarly, in [9], the authors put forward a system to forecast the wellness state of tomato plants. In order to determine if a plant is growing in healthy conditions, abiotic factors such as temperature, soil moisture, and humidity are considered. Using a soil moisture sensor and a temperature/humidity sensor, the system was able to detect soil moisture and soil humidity. SVM and Random Forest two supervised learning algorithms in addition to K-means clustering, an unsupervised learning technique were tested in order to evaluate their efficacy. The Support Vector Machine model demonstrated an accuracy of 99.3%, while the Random Forest model exhibited an accuracy of 99.6% and the K-means model achieved an accuracy of 99.5%. Jawade *et al.* proposed utilizing the Random Forest Machine Learning algorithm for predicting mango plant diseases based on weather conditions. The efficacy of the proposed technique in predicting mango diseases has been demonstrated to be highly accurate [10]. A proposal by Chen *et al.* was put forward advocating for the implementation of the Internet of Things (IoT) and machine learning-assisted methods to detect rice blast disease [11]. The transformation of data derived from images of rice fields into hyperspectral data, so that a machine learning model can be utilized to detect rice blast disease, is hereby proposed.

In [12] author recommended that an Internet of Things-based early warning system be implemented to detect signs of disease in crop fields, utilizing machine learning

**Table 4.** Summary of various crop disease

| Types of Data | Method | | Crop | Data | Accuracy |
|---|---|---|---|---|---|
| IoT data | TML | HMM | Grape | Temperature, relative humidity and leaf humidity | 90.9% |
| | | SVM | Rose | Temperature, humidity and brightness | - |
| | | Naive Bayes Kernel | Multiple | Soil and environmental data | - |
| | | KNN | Multiple | Soil and environmental data | 95.9% |
| | | Goidanich model | Vine | Temperature, humidity and Rainfall | - |
| | | Random forest | Tomato | Temperature, soil moisture and humidity | 99.6% |

for comprehensive monitoring. In [13] proposal seeks to utilize the Internet of Things and Machine Learning technologies to detect fungal diseases. Crop field environmental conditions are monitored using the Internet of Things. A prediction of the occurrence of a disease is based on the directly observed environmental conditions of fungal disease. Syarif *et al.* suggested researching the correlation between weather conditions and disease population in regard to corn crops, as well as proposing a regression model that could help further explain the correlation. This method has been developed to aid in recognizing the emergence of a particular ailment at a specified time [14].

Table 4 is a summary of the research studies presented previously and graphically it is presented here.

## 4 Analysis and Discussion

This section discusses early disease predictions made using data analysis techniques using the methodology described in Sect. 3, which was undertaken through the use of data analysis techniques. This study examines the computational efficiency of each study using multiple techniques, datasets, and parameters and considering various approaches. Various diseases and crops were analyzed under different conditions. It is also observed that every crop requires specific sensor depending on the symptoms of diseases. However, according to Classen et al. [22], the number of models is still lacking in making evaluations regarding the impact of a changing climate on plant health, as well as the direct and indirect effects and interactions that arise in consequence, a formal and comprehensive analysis must be conducted. This study, therefore, provides an analysis and classification of algorithms applied to crop and plant diseases in order to accurately identify any problematic issues, a comprehensive evaluation of the methods and techniques

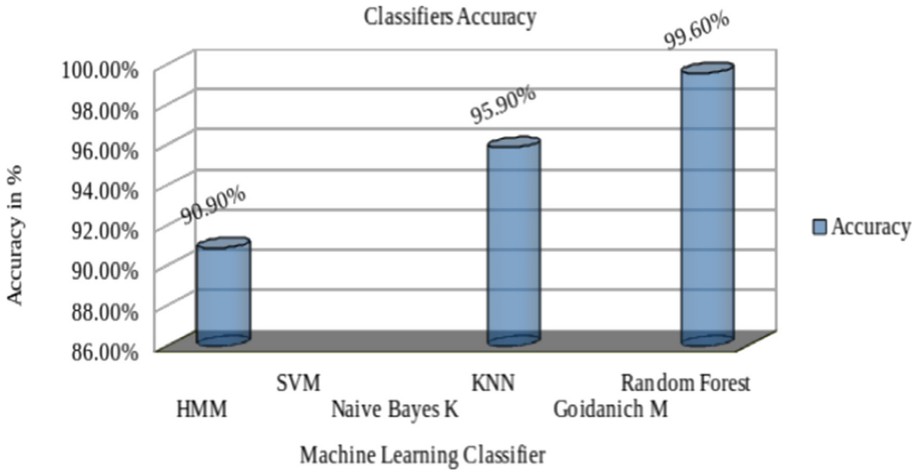


**Fig. 1.** A graph shows the best-performing machine learning algorithms.

employed, as well as the data utilized. It has been reported that there are several ways in which plant diseases can be predicted in the literature. The findings of this review cover crop and plant disease prediction models that are based on sensors and machine learning algorithms in order to anticipate symptoms before they manifest in the field or in their nascent stages.To illustrate the performance of each algorithm, a column graph was constructed (Fig. 1) showing the best-performing machine learning algorithms. This study highlights the importance of automated tools for assisting end users in the detection of plant diseases without the need for human assistance.

## 5 Conclusion

This paper intended to share an original methodology to address the association of the detection disease, pest occurrences and climate using machine learning and IoT. In order to make more accurate predictions, multiple sensor data can be associated together to gain insight into the development and wellbeing of the crop. Different types of weather sensors are commonly utilized for the detection of diseases, such as temperature sensors [15], humidity sensors [16], soil moisture sensors and light intensity sensors [17]. In order to predict crop diseases earlier in their development, ML algorithms can be used to process the multi modal data sources. The information herewith will certainly benefit agronomists to take several preventive measures in order to increase productivity and quality through effective disease management. The development of prescriptive models is necessary in the near future, and will be highly in demand.

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