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Iot And Machine Learning Based Effective Plant Disease Classification And Detection For Agricultural Applications

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ABSTRACT

Plant diseases are a key source of diminished productivity and farmer income. Researchers are now working to develop a mechanism for automatically detecting plant disease. A number of plant disease identification studies are under ongoing. Plant disease diagnosis may help farmers not only increase yields but also promote a variety of agricultural approaches. Using machine-learning algorithms, this study aims to develop a novel technique for forecasting plant illnesses. Following the detection and recording of the infected zone, image pre-processing is carried out. Following that, the pieces are gathered, the infected location is recognised, and feature extraction is carried out. Accurate plant disease identification may assist in the fast finding of a treatment to reduce loss. The results of the tests imply that plant diseases might be diagnosed and prevented earlier.

Keywords: Machine learning, Plant disease, agriculture, algorithm

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1. INTRODUCTION

In India, farming is a prominent occupation. All countries' economy depends heavily on agriculture. The main goal of agriculture development is to supply the requirements of the rising population. In the present environment, agriculture has to be modernised to survive. Both bacterial and fungal infections may destroy crops. Farmer productivity is significantly impacted by this [1]. A healthy crop is necessary for optimal productivity. Identifying diseases with our unaided eyes will always be challenging. The farm has to be watched over frequently to achieve this. This process takes a long time [2]. When the farm is vast, this is also quite costly. Even agricultural specialists struggle to quickly identify the ailments and develop a cure due to their intricacy. Automated plant disease detection technology would be very helpful to farmers. Farmers might be alerted using this technology at the proper moment, allowing them to take the necessary safeguards [3]. Different plant diseases may harm the leaves, fruits, seeds, and other parts of the plant [4]. These illnesses only affect certain plant body parts. The greatest important part of the plant is its leaves. The life cycle of a plant gets thrown off when one of its leaves contracts an infection. The leaves are often harmed by bacterial, fungal, and other diseases. Premature discovery of plant disease is thus essential. Pictures of infected leaves are shown in Figure 1.

Artificial intelligence seems to provide a better answer to this issue. Numerous ML algorithms are described to inevitably recognize and categorize plant diseases using digital plant pictures [5]. The leaf, stem, seed, and fruit are only a few of the parts of a plant that are affected by diseases. Various diseases affect distinct parts of the plant body. Only with the assistance of leaves, which are often considered as the main component of the plant, is the process of photosynthesis possible. A plant's life cycle is immediately impacted if a leaf is prone to disease. It is vital to have a system that automatically recognises and categorises the ailments in order to combat these diseases bravely. ML is probably a good option for handling this issue [6]. For the purpose of recognising and categorising plant diseases using plant images, a number of machine learning techniques have recently been described. Even though these automated methods have solved the obstacles, the reliability and consistency of the test results are still a significant problem. In this article, methods for machine learning are used to detect plant disease [7]. The plant has been photographed and is now ready to be captured digitally. Then, extraction approaches including edge recognition, colour interplanetary, and textural aspects are used. The attributes that have been gathered are fed into the classifiers. In this study, image processing is used to determine the ill cotton leaf area [8]. The authors demonstrated how to colour convert an input colour picture. Using a threshold setting, the green pels in the picture are buried and eliminated. The segmentation operation is then finished. All trustworthy segments are used to calculate the texture statistics. To categorise diseases, use the classifier below. In this study, the authors compare and assess several image processing classification algorithms. reported segmentation-based techniques[9].

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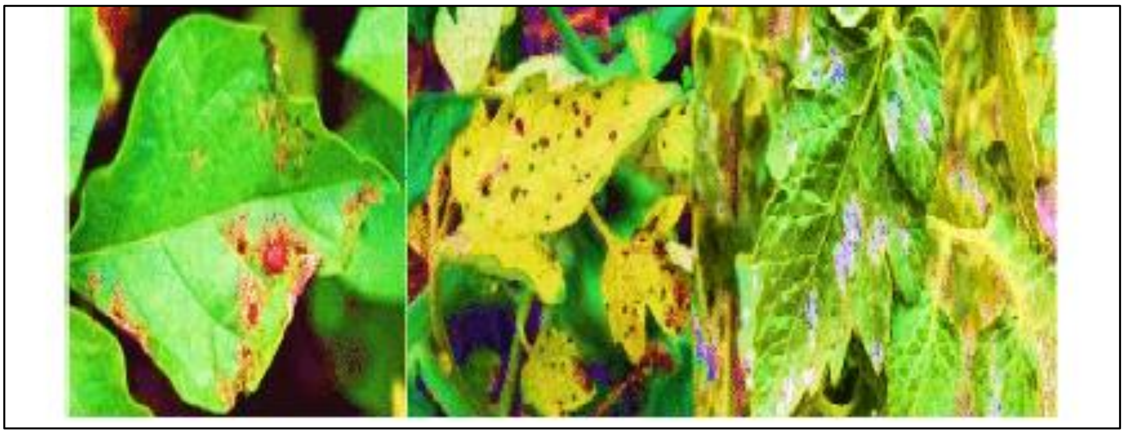

Fig. 1. Plant diseased leaf

In another research, they used a method that included first categorization and then marking the citrus fruits. To establish the kind of fruit, the photos of the fruits are combined. They used a neural network (ANN). The Gabor filter is used to extract characteristics that are then classified using an ANN classifier. Color and texture elements were also used [10]. The researchers used a threshold and a Gaussian filter to reduce noise in order to get the green component. An image processing strategy is provided for recognising the jute plant disease. This method might be used to detect sick stems in jute plants. Another study discovered that employing colour picture processing to maintain visual cues of plant diseases was beneficial [11]. The translated picture is first divided into portions based on histogram intensity distribution. When focused on a single picture with a wide range of brightness, this strategy comes in handy. When the segmentation procedure is finished, the recorded region is optimised to remove pixel parts that do not belong in the target area. The results satisfied all requirements and correctly identified the plant's sick zones. They demonstrated an image processing method for detecting unhealthy plant regions. After the initial photo, colour correcting is applied. The Gaussian filter is used to previously modified photographs. The region of interest is then located using segmentation. The position of the appropriate threshold aids in group distinction [12]. The segmented areas are then classified and labelled as healthy or dangerous using the SVM classifier. It is advised to experiment with various image processing-based detection techniques. The authors employed genetic algorithms to detect plant diseases. On-site expert leaf inspection, which allows for the diagnosis and proof of identity of plant diseases, is the only disease detection method now in use. This technique is more costly on larger farms since it requires a large team of professionals and continuous plant monitoring [3]. Only a few countries lack adequate agricultural infrastructure. As a consequence, they consider employing experts to be vital. However, this leads in time- and money-consuming duties. In such settings, this proposed approach has been shown to be useful for calculating large crop yields. Checking the condition of the leaves may help to detect plant sickness sooner, which is less expensive and more effective [2]. By allowing robot navigation, inspection, and image-based autonomous process control, this improves machine vision. It requires more time and effort to visually identify leaf diseases. This work,

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on the other hand, is less precise and can only be completed in particular locations. In contrast, non-manual, automated plant disease detection is quicker, more accurate, and easier to use.

2. Methodology

Plant leaves may be affected by a variety of diseases. This might be due to environmental factors such as humidity. Bacterial infections, fungal diseases, and viral illnesses are the most common. This might result in a change in the colour forms. Because of their comparable patterning, these changes are difficult to discern. As a result, early diagnosis of some conditions may prevent loss. This research proposes a deep learning technique for classifying plant diseases.

The various steps of the proposed research are shown below

Step 1: The plant's leaf is photographed first. The picture uses the RGB colour model.

Step 2: Pre-processing is done to minimise noise and improve picture quality. Contrast enhancement is used to pre-process the photos. By converting input intensity to a new value, it improves visual characteristics by increasing image contrast.

Step 3: This is the most important step for categorising photographs. Rather of choosing the whole scene, we just collect attributes from the affected zone. To extract attributes, the grey co-occurrence matrix (GLCM) is employed. It establishes a photograph's spatial variation in fray level. Some picture properties, such as contrast, correlation, energy, and homogeneity, may be recovered using GLCM. Several properties are retrieved using Matlab commands, including Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, and Skewness.

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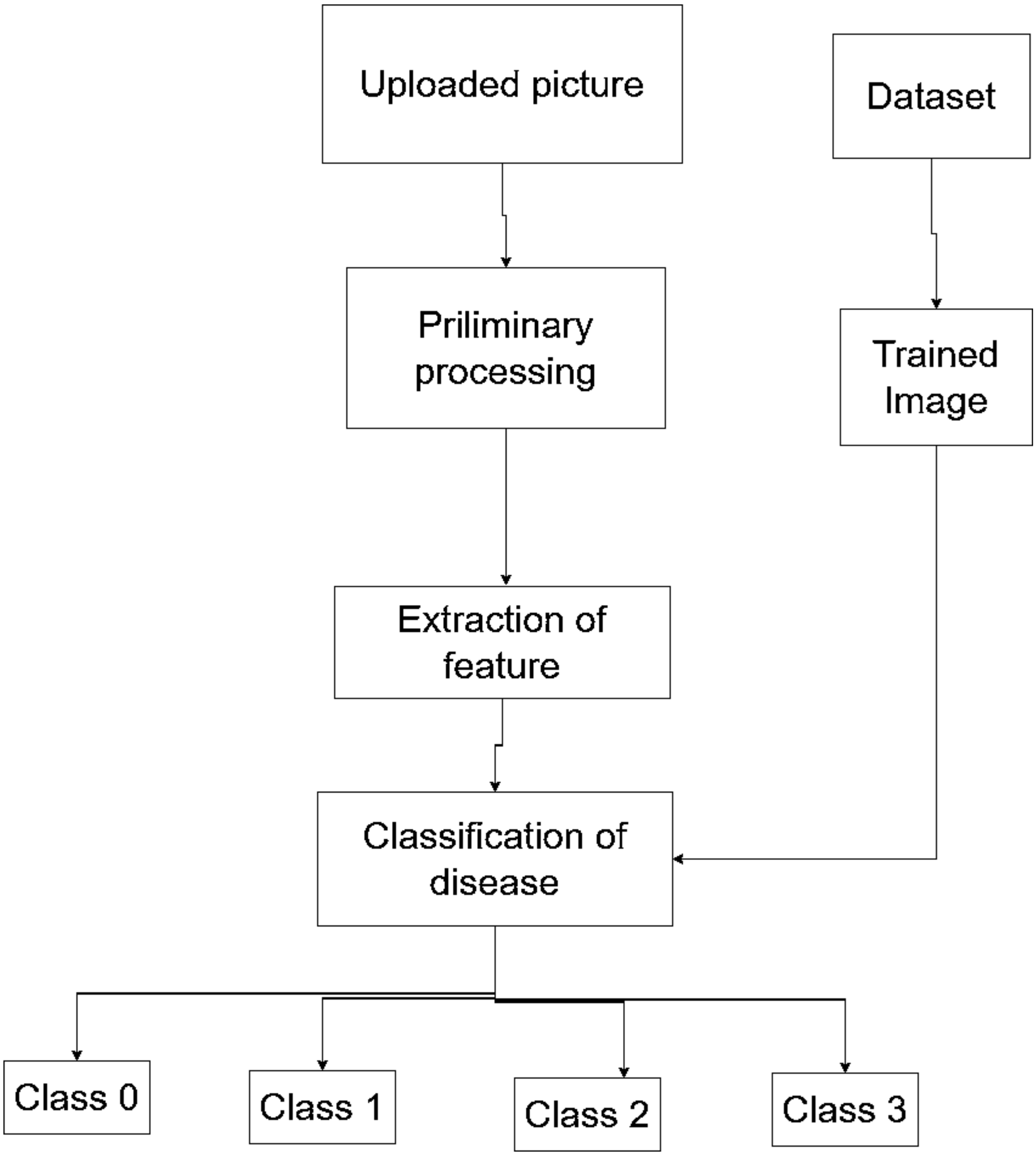

Fig. 2. Flow chart of the proposed work

Step 4 A data collection of photographs of plants with different illnesses and images of healthy leaves is collected from the internet and used for training.

Step 5: The classifier is trained using the sample input leaf shots, which include both infected and healthy images.

Step 6: The data is divided into k distinct categories. The given picture is first transformed to LAB space. The K-means approach is divided into two phases. The first step is to locate the k-centroids. The next step is to assign each new item to one of these clusters based on its proximity. Because of the way the pieces are arranged, the items inside the clusters have comparable qualities. The distance unit employed in this context is the Euclidian distance. The equation below is used to calculate the distance between points p and q.

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D(p,q)=$\sqrt{\sum_{i=1}^{n}(pi-qi)^2}$

The data points in this case are p and q.

Step 7 In this situation, the classifier is the support vector machine (SVM). It is a hyperplane-based binary classifier. We'll choose the samples closest to the border. It categorises the classes using a variety of kernels. Many classes are classified using one to one or one to many mapping. The highest output function determines the class. Two classes were classified using the standard SVM. In actuality, segmentation into many categories is required. To categorise the illnesses, the proposed technique employs many SVMs.

The DHT22 (thermal sensor) and KG003 (soil moisture sensor) sensors are combined with the Raspberry Pi3 model in agricultural situations. Thermal, moisture, and soil wetness content are measured on a regular basis and transferred to the cloud, which acts as a information store for later use. The DHT22 is a low-cost digital temperature and humidity sensor. A thermistor and a capacitive humidity sensor were used to monitor the ambient air, and a numerical output signal was given on the information pin (no analogue input pins needed). Despite its ease of use, data collecting needs precise timing. A sensor known as the KG003 is used to detect soil moisture. If the soil has a low water content, the module's output is high; otherwise, it is low. The insulator constant influences the moisture content of the soil. When soil moisture exists as free water, capacitance studies between two electrodes buried in the ground indicate that the insulator constant is linked to the moisture content (as in sandy soils). To test the insulator constant, frequency stimulation is applied to the probes. Although the probe's output is not directly connected to soil moisture content, it is affected by soil type and temperature.

3. Result and Discussion

The training dataset for this algorithm is images from the internet. Characteristics are gathered from the first few images picked from this collection. We created four classes. Alternaria Alternata is represented by Class 0, Anthracnose by Class 1, Bacterial Blight by Class 2, and Healthy Leaves by Class 3. The sickness is also represented by Class 0. Figure 3 depicts the results obtained following the preprocessing step.

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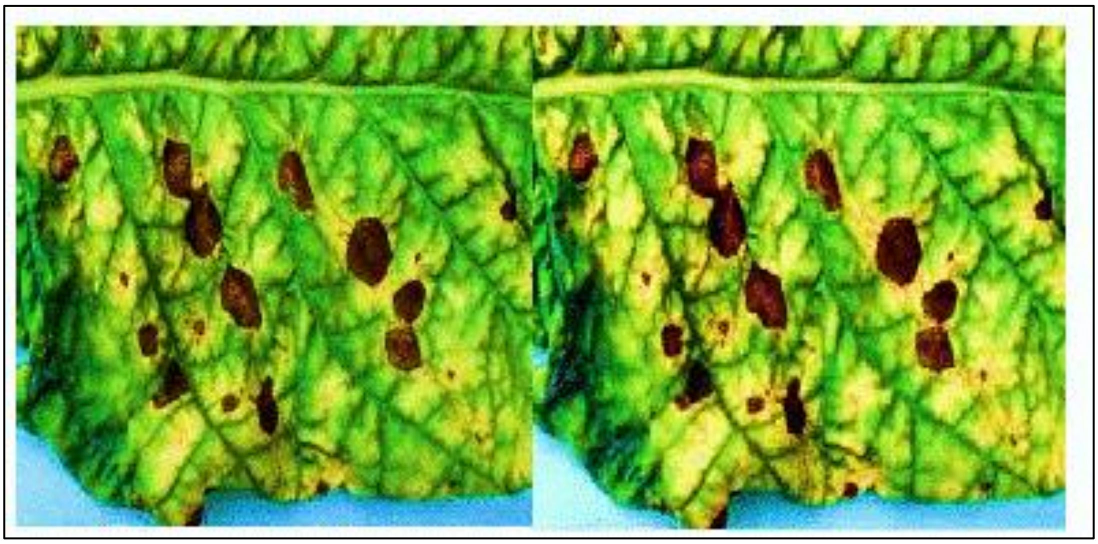

Fig.3 Uploaded image for processing and the contrasted version on the right side for disease identification

Figure 4 shows the findings of sickness classification. The picture shown is of a leaf with Alternaria Alternata on it. The classifier successfully categorised Alternaria Alternata as class 0.

Fig. 4 Uploaded image and identified disease

The supplied picture shows a leaf with anthracnose. The classifier successfully recognised anthracnose as class 1.

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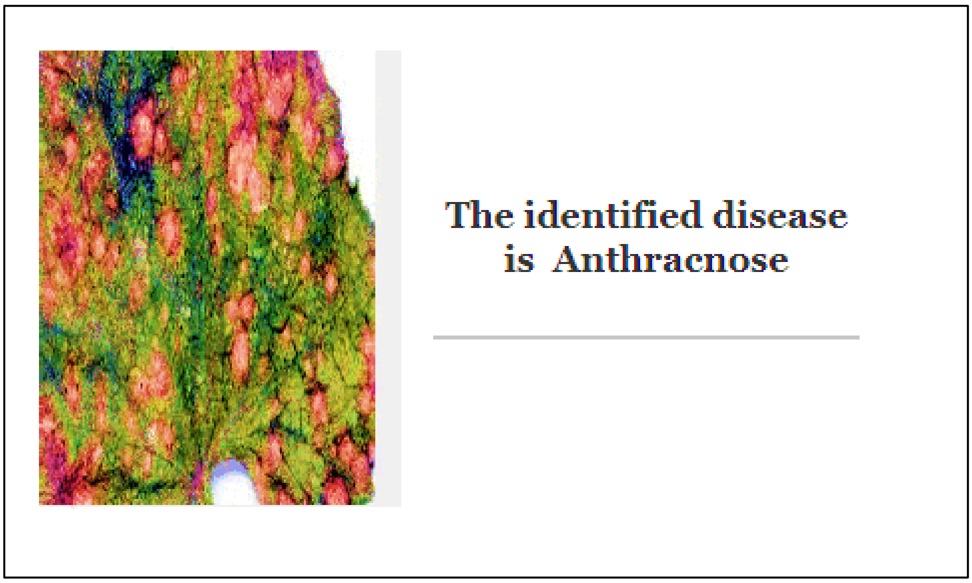

Fig. 5 Uploaded image and identified disease

CONCLUSION

Today, technology is used in many facets of life. Plant sickness manual diagnosis is a challenge for farmers. Farmers also don't have simple access to legal advice. An automated method for detecting plant diseases is useful for the farmer for the early prediction and identification of the disease. Properly identifying disease is much important to give the proper pesticide for the plant. In this research machine learning based disease identification method is proposed. This proposed method works by the images of the identified plant disease. The temperature and soil moisture sensor detects the surrounding condition of the plant. By this way the health of the surrounding as well as the plants are monitored using internet of things.

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