International Research Journal of Education and Technology
Peer Reviewed Journal
ISSN 2581-7795

AGRI ROBOT

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Abstract - The productivity of agriculture significantly affects the Indian economy. To increase production in agriculture, plant disease identification should come first. The key to lowering agricultural product output and volume losses is early detection of unhealthy plants. A thorough examination of the plant's outward characteristics is required for the research of diseases that affect plants. For sustainable farming, keeping an eye on the health of the crops is crucial. At best, manually tracking plant disease outbreaks is challenging. The method calls for a tremendous amount of work, knowledge of plant diseases, and processing time.

Early detection is essential since delaying it can have a major negative influence on the output's quantity and quality. Utilizing an automated method will be helpful to monitor crops on large farms as soon as they are evident on the plant's leaves. It is possible to identify plant illnesses as a result by using image processing. The approach for detecting diseases entails a number of image processing phases, such as image capture, pre processing, segmentation, feature extraction, and classification. This study sought to identify plant illnesses using images of plant leaves. This study looked at techniques for identifying plant illnesses by

analysing pictures of the leaves. A few methods for choosing and extracting features in order to identify plant diseases were also covered. Neural networks were employed in this study to identify and categorise leaf diseases. This was done with the help of a piece ofhardware called the AGRI ROBOT.

INTRODUCTION

In a time of climate change and increased international trade, recent epidemic outbreaks highlight the significance of the search for effective diagnostic technologies for plant pathogen identification and management. Crop losses are linked to production conditions, with losses being higher in food insecure places (with emerging and re-emerging pests/diseases) and lower in those with food surpluses, according to research published in other journals that has been extensively researched. Modern technologies have the ability to produce enough food to meet the demands of more than 7 billion people. We needed a substantial, verified dataset of photographs of both healthy and ill plants for the detection of plant diseases in order to build precise image classifiers. Until recently, neither such a dataset nor even smaller ones were publicly available. The decrease in analysis expenses is another important consideration given the huge number of plants that are typically included in monitoring programmes. Response periods would be substantially shortened by the development of on-field molecular techniques, which would stop illnesses from spreading to other plants or being introduced into new areas. The most common plant diagnostic techniques are briefly discussed in this paper before focusing on newly developed sensors that have the potential to fundamentally transform how phytopathologists approach theirwork.

I. METHODOLOGY

In each of our trials, we use one of three different iterations of the whole PlantVillage dataset. We conduct all of the experiments using a version of the PlantVillage dataset where the leaves have been segmented, eliminating all additional background data that might have the potential to introduce some inherent bias into the dataset because the PlantVillage dataset was collected using a regularised process. We execute all the tests on a version of the PlantVillage dataset after first experimenting with a grayscale version of the dataset and then starting with thePlantVillage dataset in its original colour. With the aid of an automated script tailored to our particular dataset, the segmentation procedure was carried out. Based on a set of masks generated by study of the colour, brightness, and saturation components of various image components in multiple colour spaces, we chose a technique (Lab and HSB).

During one of the processing stages, we were able to easily fix colour casts that were particularly noticeable in a few of the dataset's subgroups, removing yet another potential bias. Point-of-care (POC) diagnostics tools must be able to conduct analysis and provide prompt responses outside of the laboratory in order to achieve early diagnosis, meet surveillance goals, and prevent large production losses. Whatever advantages a procedure may have (sensitivity, validity, and repeatability of results), it may still take a long time to complete, require significant equipment, qualified personnel, and cost a lot of money.

FIGURE 1 | For each crop-disease pair, an illustration of a leaf image from the PlantVillage dataset was used. The fungus Venturiainaequalis, sometimes known as apple scab Apple black rot is sometimes referred to as Botryosphaeriaobtusa.

(3) Apple cedar rust (Gymnosporangiumjuniperi-virginianae) (4) Corn Common Rust, Pucciniasorghi (5) Blueberry (6) Cherry (7) Cherry Powdery Mildew, Podoshaera clandestine (9) wholesome corn (10) wholesome corn (11) Exserohilumturcicum, the northern cause of cornleaf blight (12) Grape Black Rot caused by Guignardiabidwellii (13) Grape Black Measles, Phaeomoniellaaleophilum, and Phaeomoniellachlamydospora (Esca). (14) Healthful grapes (15) Xanthomonascampestris, the peach bacterial spot CandidatusLiberibacter spp. (16) Orange Huanglongbing (Citrus Greening) (17) Grape leaf blight (18) Peach health

(19) Bacterial Spot on Bell Pepper (20) Xanthomonascampestris(20) Bell Pepper in Good Health (21) AlternariaSolani, (22) Good Potatoes, and (23) Phytophthorainfestans, Potato Late Blight (24) Good Soybeans, (25) with Raspberries

(26) Erysiphecichoracearum, Powdery Squash Mildew (27) A wholesome strawberry Strawberry leaf scorch or Diplocarponearlianum (30) Alternariasolani's early tomato blight (31) Phytophthorainfestans' late tomato blight (32) Passalorafulva's mould on tomato leaves (33) Tetranychusurticae's tomato two-spotted spider

mite (34) Septorialycopersici's tomato septoria leaf spot (35) Target Spot on Tomatoes Caused by Corynesporacassiicola (36) Tomato Yellow Leaf Curl Virus (38), Tomato Mosaic Virus (37), and Healthy Tomatoes.

Table 1: compares the primary methods for identifying plant diseases and related traits. PCR stands for polymerase chain reaction, whereas FISH and ELISA stand for enzyme-linked immunosorbent assay, immunofluorescence and flow cytometry, respectively. Colony forming unit(CFU)

III.IMAGE SEGMENTATION

Image segmentation is a technique for breaking up an image into smaller versions. Here, we apply the K-mean segmentation algorithm, which divides and clusters the image using hue estimation. We choose the cluster image displaying the diseased area for feature extraction since the green colour of the leaves is normal. The segmented images of the leaves are seen in below.

By using the Euclidian distance measurement and the K-means clustering algorithm, the data vectors are divided into clusters based on how close together the pixels are. Cluster centroids have randomly chosen beginning values and have dimensions according to data vectors.

IV. FEATURE EXTRACTION

Feature extraction is the process of extracting pertinent information from an image's interesting portions. The region of interest's (ROI) dimension will be smaller than the image's original size. One of the best techniques for texture analysis is the grey level co-occurrence matrix (GLCM). It estimates the image properties using second order statistical methods. The GLCM algorithm determines where in the image a pixel with a specific intensity or grey value appears. The total occurrence of pixels with a particular intensity in the spatial domain will be the resultant.The size of the GLCM will depend on the number of grey levels.

V.CLASSIFICATION

Diseases brought on by fungi, bacteria, and villises impact leaves. Insects can sometimes cause leaf damage that manifests as a disease called leaf spot. Depending on the stage and organism involved, the diseased portion of the leaf will vary in size and colour. Spots will be seen in a variety of colours, including yellow, brown, tan, and black. The disease is categorised using the GLCM texture information. We categorise the illness as

Anthracnose, Cercospora Leaf Spot, and Bacterial Blight in this instance.

VI. DISCUSSION AND FUTURE PERSPECTIVES

A review of current methods for spotting plant diseases as well as an overview of cutting-edge approaches for seeing symptoms and taking preventative measures against pathogen transmission have been given. We also compiled developments in sensor and microfluidics technologies, taking into account more recent developments in wearable sensing and Internet of Things (IoT) technologies. Thanks to the fusion of multiple bio-sensing platforms within smartphone-integrated electronic readers, new perspectives are now becoming apparent.The integration of skin-like flexible sensors with wireless communication technology for real-time plant monitoring is an intriguing angle.Instead,

new "lab-on-a-drone" analysis platforms could be created through the fusion of sensing and robotics technologies. These platforms would enable quick in-flight assays with smartphone connectivity, do away with the need for sample collection and analysis, and enable scenarios for emergency response, agricultural bio-surveillance, and veterinary field care. For in-field nucleic

acid-based diagnostics, Priye et al.Achieved flight replication of Slaphylococcusaureus and A-phage DNA targets in less than 20 min utilising a consumer-class quadcopter drone with smartphone connectivity With connectivity,

high-quality photos, and processing power, smartphones can also assist develop more precise, intelligent, and portable diagnosis tools which could aid institutions and farmers worldwide in the fight against plant diseases. All of these technologies are able to communicate with one another, creating new opportunities for effective and intuitive plant pathogen control. In addition to the aforementioned technological developments, interdisciplinary methods like Climate-Smart Pest Management (CSPM) are also becoming available, with the implementation of comprehensive strategies that include farmers, extension agents, researchers, and public and private sector stakeholders, acting in concert to increase the resilience of farms. Due to a strong linkbetween research and the public/private sector, this approach can overcome a number of obstacles.

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