A SURVEY ON DIFFERENT TECHNOLOGIES FOR DISEASE AND PEST DETECTION IN PRECISION AGRICULTURE

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Abstract

The development of a nation is mainly based on farming. Bread is the most important nourishment for human well-being. It established that plants being the start of sustenance, significantly experienced few infections. It would hit us strongly if we did not properly care for plants. In this paper, innovation thrives entirely.

Nonetheless, it is not possible to farmers to use the expert's service recommendation because of monetary regulations and additional information and difficulties in travelling for treatment. To inform the farmers about the plant's diseases from the expert is tedious. The fastest and most accurate identification of plant diseases will help the farmers from losing yield. The Deep Learning method is the best because it does not need people interaction, even as capturing images, function extraction etc. It has more benefits over different methods like Machine Learning algorithms that could solve properly established troubles. But for more fantastic, more excellent complicated facts packages, we need Deeper Architectures and as. As a result, the new technique includes using a Convolutional Neural Network to discover and analyse plant illnesses like Black measles, Scab, Early blight, Leaf scorch and Bacterial spot.

Keywords: IoT, Sensors, smart agriculture, deep learning.

I INTRODUCTION

Agriculture is a zone that has a significant influence on the existence and financial status of people. Horticulture is to be an essential wellspring of 58% of India's population. India is in the following position worldwide in expressions of farm yields. In 2018 proposed that cultivating pushed work for more than half of the representatives, thus adding to 18-20% of us of a's Gross domestic product. India has proved to be one of the top international locations in agricultural yield and productiveness. Most people of the population are in agriculture. So, it's miles very vital to understand the issues faced in this region. In agriculture, many problems meet, like pointless cultivating cycles and procedures, lack of manure, compost, and composts, insufficient water supply, and different disorders going after vegetation. Diseases are harmful to the safety of plants. That influences its increase [1]. The attack of those illnesses on plant life results in a significant loss in high-quality and quantity yield.

The primary milestone in agriculture is the automatic detection of plant disease based on plant leaves. Moreover, early plant disease detection undoubtedly influences crop yield and quality [2]. Since traditional guides may be very time taking and extra liable to inaccuracy and turn incorrect results. The latest development in technology and this enlargement have made it easier for plant illness prediction and identification of pests, giving the best treatment for agriculture if any plant has a diseased situation. This paper figuring out leaf disease of plants is centred on 14 different plant life, including soybean, squash, strawberry, tomato, cherry, grape, orange, peach, pepper, potato, and raspberry. This gadget is constructed on standards; deep studying Convolutional Neural Networks are published in developing a statistical version performed at the entered photo and transforming the input to categories output tags.

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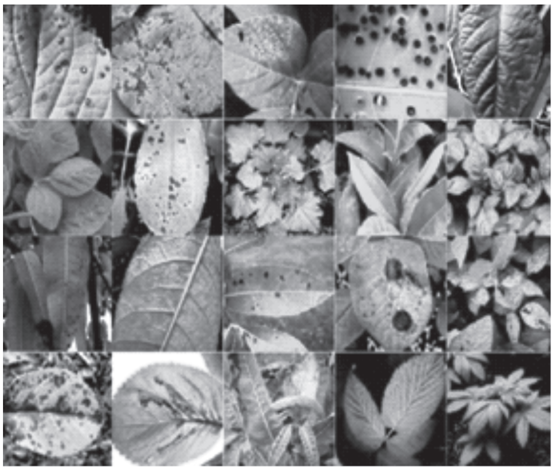

Fig:1 Disease Plant Leaves

II RELATED WORKS

With the help of Digital Image Processing and Machine learning algorithm, much research has been undergone to identify plant diseases. In this part, only a few of them are summed up. The author in [3] proposed an inference system using a Raspberry-Pi stage and incorporates a camera for securing trap pictures and an Intel Neural Compute Stick for assessing the DNN. One-range availability is ensured by a LoRa modem appropriate for low-bitrate communications. To broaden the battery life of the framework, the model likewise coordinates a total sun-based energy reaper, as another sun-based reaping remote shrewd cameras. In this beginning phase, it is executed utilising a Pi-Juice-Hat that gives all parts to deal with a low-power stage. Even more explicitly, a low-power RTC clock is used to awaken the framework, and a voltage screen guarantees enough energy is put away in the battery. The model created is conservative (101×67×55 mm), versatile, and simple to introduce. The gadget can be introduced inside ordinary pheromone-based snares. Codling moth location is executed double a day.

In this paper [6], utilising CNN innovation to apply "earlier information" to the learning system upholds tackling the little examples of harvest infections. The fundamental rule is as per the following. With the exchange learning (TL), the "earlier information" obtained from "non-single" datasets is applied to CNN preparing of space explicit acknowledgment to reduce the over fitting issue brought about by lacking information volume in a particular area. In this paper, TL arranges crop sicknesses to apply the helpful abilities gained from at least one helper space assigned to the new targets and errands. Most of the exploration where the TL strategy is used to acknowledge harvest infections depends on the TL technique for boundary adjusting. The blend of a depth-wise divisible convolutional organisation and move learning. Admitting yield and disorders can further develop acknowledgment exactness and illness acknowledgment. It can likewise be applied to thoughtful, intelligent terminal gadgets in a superior manner.

Eftekhar Hossain [4] presents a framework for perceiving plant disease with reasonable division K-Nearest Neighbor. Elements that were brought out through pictures of the diseased view helped to bring out through images of the diseased view helped kill the arrangement. In the paper, the framework KNN division dissects the diseases usually found in plants, like bacterial blight, early blight, bacterial spot, and leaf spot of different plant species. This technique introduced an accuracy of 96.76%.

III METHODOLOGIES

Different disease-related problems and seizures impact plants. There are a few causes that their effect on plants can describe unsettling influences because of ecological circumstances like temperature, stickiness, unreasonable or lacking food, light and the most well-known disease like bacterial, viral, and fungal disease. In this proposed framework, we use CNN calculation[5] to distinguish disease in plant leaves because, with the assistance of CNN, the most fantastic accuracy can be accomplished, assuming the information is excellent.

A. Sensor Data

We utilise the Plant village Dataset. The Plant Village dataset contains 54303 sound and undesirable leaf pictures isolated into 38 classes by species and disease. We dissected over 50,000 images of plant leaves with appropriate labels from 38 categories and attempted to anticipate the class of diseases. We resize the picture to 256x256 pixels and performance enhancement and model predictions on this compressed picture.

Class	Plant Name	Disease Name	Causes Virus Name	Types of Disease	No. of Images
C1	Apple	Healthy	-	-	1645
C2	Apple	Apple scab	*Venturia inaequalis*	Fungus	630
C3	Apple	Black rot	*Botryospaeria obtusa*	Fungus	621
C4	Apple	Codar apple rust	*Gymnosp-orangium*	Fungus	275
C5	Blueberry	Healthy	-	-	1502
C6	Cherry	Healthy	-	-	854
C7	Cherry	Powdery mildew	*Podospaera clandestina*	Biotrophic Fungus	1052
C8	Corn	Healthy	-	-	1162
C9	Corn	Cercospoea leaf spot	*Cercospora zeae-maydis*	Fungal	513
C10	Corn	Common rust	*Puccinia sorghi*	Fungal	1192
C11	Corn	Northern leaf blight	*Exserohilim turcicum*	Foliar	985
C12	Grape	Healthy	-	-	423
C13	Grape	Black rot	*Guignardia bidwell ii*	Fungus	1180
C14	Grape	Esca (Black Measles)	*Phaeomoniella chlamydosporia*	Fungus	1383
C15	Grape	Leaf blight (Isariopsis)	*Pseud ocerospora vitis*	Fungus	1076
C16	Orange	Healthy	-	-	5507
C17	Peach	Healthy	-	-	360
C18	Peach	Bacterial spot	*Xanthomanas campestris pv, pruni*	Bacterial	2297
C19	Pepper / bell	Healthy	-	-	1487
C20	Pepper / bell	Bacterial spot	*Xanthomanas campestris pv*	Bacterial	997
C21	Potato	Healthy	-	-	152
C22	Potato	Early blight	*Alternaria solani*	Fungal	1000
C23	Patato	Late blight	*Phytophthora infestans*	Fungal	1000
C24	Raspberry	Healthy	-	-	371
C25	Soyabean	Healthy	-	-	5090
C26	Spuash	Powdery mildew	*Podophaera xanthii*	Fungal	1835

Table 1. A detailed description of the Plant Village Dataset with related information [7,8,9,10,11]

B. Classification

The point of this review was to draw an examination of the order exactness of five distinct, profound learning models. For the fake informational collection, a multi-class arrangement was performed through the paired account on the informative index, for example, sound Vs. Unfortunate.

Class	Plant Name	Disease Name	Causes Virus Name	Types of Disease	No. of Images
C27	Strawberry	Healthy	-	-	456
C28	Strawberry	Leaf Scorch	Diplocarpon carlina	Fungal	1109
C29	Tomato	Healthy	-	-	1591
C30	Tomato	Bacterial Spot	*Xanthomonas perforans*	Bacterial	2127
C31	Tomato	Early Blight	*Alternaria'sp.*	Fungal	1000
C32	Tomato	Late Blight	*Phytophthora infestans*	Fungal	1909
C33	Tomato	Leaf Mold	*Lycopersicon*	Fungal	952
C34	Tomato	*Septoria Leaf Spot*	*Septoria lycopersici*	Fungal	1771
C35	Tomato	Spider Mites	*Tetranychus spp.*	Pest	1676
C36	Tomato	Target Spot	*Corynespora cassiicola*	Fungal	1404
C37	Tomato	Tomato Mosaic Virus	*Tomato mosaic*	Viral	373
C38	Tomato	Tomato Yellow Leaf	*Begomovirus*	Viral	5357

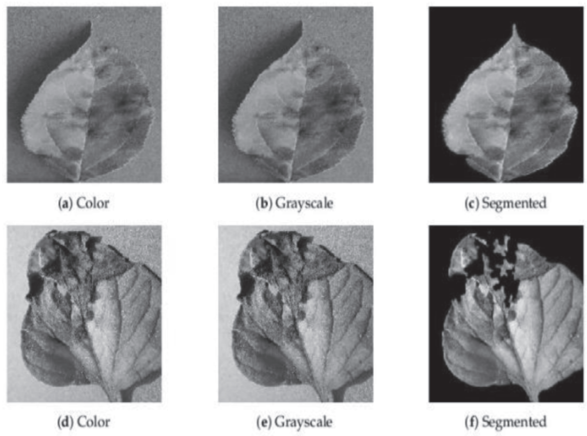

Fig 2. Sample image of colour, grayscale and segmented of Plant Village image dataset. [11,12,13]

IV KEY TECHNOLOGIES

A. Deep Learning

Deep learning is a type of machine learning it uses various layers to extract data from a complicated dataset and to raise them into a high position. It uses data filtration between the layers. Deep learning filters the data the same as the human brain can. Many deep learning strategies utilise the neural network structure. The term “deep" refers to the different secret layers in the neural network. The deep neural network has more hidden layers than a conventional neural network.

B. Convolutional Neural Network

There are different types of deep neural networks. Convolutional Neural Networks are one of them. A Convolutional Neural Network greatly consolidates and highlights input information, and afterwards, it utilises 2D convolutional layers. Consequently, this structure is reasonable for handling 2Diamentional information, similar to pictures. CNN's cancelled the interest in manual element removal and filtration of the order to the images. The CNN model of its concentrates incorporates straightforwardly from photos. The features taken out need to be pre-prepared; they are around read while the association is prepared on several get-togethers of images. The Convolutional Brain organisation (CNN) model has different layers that execute the picture's treatment in convolutional layers, consolidating the Information layer and yielding the Layer. Convo Layer. Completely. Delicate max layer, Associated layer. Pooling Layer.

C.VGG 16 Model

A CNN model used for large-scale images is VGG16. The best way to identify plant diseases is to complete two tasks. The first step is object localisation, detecting objects in an image that comes from various classes. The second is picture classification, which involves labelling each image with one of the multiple categories. There are seven distinct layers in the CNN model. Certain information is handled in each layer. Here are those seven layers: Convolutional layers with fully connected, Soft-max, input, output, and pooling layers.

Input layer: It includes data in the form of images. The dimensions have the image's height, width, depth, and colour information (RGB). The input size is a 224 x 224 RGB image.

Convo layer: Features extraction layer is another name for the convolutional layer. This layer pulls the inescapable highlights from the given collection of images using dot products of the image dimensions.

Pooling layer: By decreasing (or) reducing the dimensions of the highlighted matrix obtained using the speck items, the pooling layer aids in minimising the computational power needed to handle the information.

Fully connected layer: Loads, neurons, and biases are all involved. It connects neurons starting with one convolutional layer and progressing to the next.

Softmax/ logistic layer: Softmax carries out multi-classification. The logistics layer carries out the binary classification. It determines the likelihood of the presence of a given object in the image. If the thing is visible in the picture, the probability is 'l'; otherwise, it is '0'.

Activation function-ReLU: It modifies the total weighted input through the node and inserts it into the activity, thereby enacting the node. Rectified Linear Unit (ReLU) is an actuation capability used in convolutional neural networks.

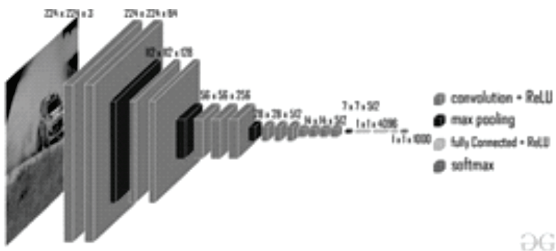

Fig 3. VGG 16 MODEL

V CONCLUSION

Farming employs a sizable portion of the Indian population. As a result, because agriculture is essential to the development of the economy, it turns out to be extremely important to distinguish and perceive the leaf diseases that result in losses. This study employs a deep learning approach called CNN to create a framework for identifying, detecting, and recognising 13 different plant leaf diseases. This method used a base layer arrangement to recognise the conditions of seven classes. The Plant Village dataset was used to train the neural network. This framework will have a graphical user interface. The client can use this GUI to select images from the dataset. The client can choose any image from the dataset, and the idea is stacked, after which the forecast is generated.

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