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PLANT HEALTH MONITORING AND DISEASE IDENTIFICATION USING DEEP LEARNING

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ABSTRACT:
One of the most significant elements that pose a significant risk to agricultural productivity is the presence of leaf diseases. Finding and naming diseases and pests as soon as they appear is one of the most effective ways to cut down on the financial damage they incur on the farmer. In this study, a convolutional neural network was utilized to automatically detect illnesses that might affect crops. Here we have taken an image dataset containing 10000 images. Training is carried out with the help of the Inception-V3 model. The direct edge in the cross-layer and the multi-layer convolution in the residual network unit of the model. Following the completion of the combined convolution process, it is triggered by the connection into the SoftMax function. The findings of the experiments indicate that this model has an overall recognition accuracy of 81.9%, which substantiates the claim that it is successful. The findings demonstrate that the system is capable of correctly identifying crop illnesses so that the farmer can choose to suitable method to overcome the crop from the identified disease.

Keywords: Tomato leaf disease prediction, deep learning, convolutional neural network, illness.

1. INTRODUCTION:

Now, researchers focusing on agricultural diseases are mostly moving in two different ways. The first way is the classic physical method, which identifies various illnesses mostly by spectral detection. This method has been around for a very long time. Different kinds of illnesses and insect pests produce different kinds of damage to leaves, which in turn leads to different kinds of spectral absorption and reflection from healthy crops and those that have been damaged by diseases [1]. The second option is to recognize pictures via the use of computer vision technologies. That is to say, the features of disease pictures are extracted via the use of technology connected to computers, and the recognition is accomplished using the distinct characteristics that sick plants and healthy plants share.

The recent years have seen a fast growth of artificial intelligence (AI), which has resulted in life being more convenient, and AI has become a well-known technology in recent years. Take, for instance, the game of Go, where AlphaGo prevailed against the reigning world champion. Deep learning is an application of artificial intelligence technology that is used in a variety of disciplines, including Apple's Siri and Amazon's Alexa, which serve as voice assistants for their respective companies. Image recognition, which serves as the primary focus of research in the fields of computer vision and artificial intelligence, has seen significant advancements in recent years. In the context of agricultural applications, the purpose of image recognition is to recognize and categorize various kinds of photographs, as well as to do analyses of the various types of crops, diseases, and severity levels [2]. After that, we will be able to devise appropriate countermeasures to deal with the myriad of issues that arise throughout agricultural production in a timely and effective way. with the purpose of further ensuring and improving the production of crops and contributing to the greater growth of agriculture.

With the fast progress of deep learning notably in image recognition voice analysis, natural language processing, and other domains, it demonstrates the one-of-a-kindness and efficacy of deep learning. Deep learning is a more effective technique for diagnosing plant illnesses than the more conventional approaches that have been used in the past. This pertains to the sector of agricultural production. The model that uses deep learning can monitor, diagnose, and stop the development of crops at the appropriate moment. Image identification of crop illnesses and insect pests might lessen farmers' reliance on plant protection technicians in agricultural production, allowing them more time to find and implement appropriate solutions to any issues that arise. The pace of manually detecting anything is far slower than the speed of identifying something using an intelligent network, which is lot quicker than identifying something artificially [3]. In addition, the precision of the recognition is always improving thanks to the ongoing development. Not only can the establishment of a reliable agricultural network and the combination of the Internet and the agricultural industry help solve problems related to crop yield that are caused by diseases and insect pests, but they can also help foster the growth of agricultural informatization [4].

However, because of the mountain environment's rough topography, the surrounding interference factors are stronger. This is a challenge for radio astronomers. As a result, acquiring a picture is a more challenging task than dealing with the overall surroundings. Additionally, the camera and network transmission that are essential for picture identification and processing will have some degree of influence on the situation. Mountainous regions provide a greater challenge for the implementation of intelligent recognition because of this reason. The purpose of this article is to conduct research on the identification model of agricultural diseases and insect pests, as well as construct a platform for the Internet of Things that can function in the challenging environment of mountainous regions [5]. This model's goal is to result in an improvement agricultural informatization, reducing the damage caused by diseases and pests to crops, and increasing crop yields are all important goals.

2. LITERATURE SURVEY

Research is ongoing in several areas, including those concerned with the detection and control of agricultural diseases and insect pests. The advancement of technology has led to the creation of a variety of sensor networks and autonomous monitoring systems that have been suggested.

Image sensors are one other kind of solution that may be used in conjunction with monitoring traps that are utilized for the purpose of capturing pests. Conceived and constructed a system that has a low power consumption and is powered by a battery [6]. The system is based on wireless image sensors. The setting and remote adjustment of the frequency of recording and sending trap pictures of sensors is something that can be done by the trapping application.

In addition, acoustic sensors play a role in the monitoring system. [7] Provides a method that may be used to identify red palm weevil (abbreviated RPW) using them. The noise that is made by the pest may be automatically caught with the assistance of an acoustic device sensor. When the sound level of the pests reaches a certain threshold, the system will send a notification to the customer informing them that an infestation is taking place in the designated region. It was helpful for farmers to save time and energy by allowing them to monitor every portion of their field on their own, which also increased the efficiency of their work. When the predetermined threshold value is exceeded, each of the acoustic sensors will report the amount of noise that they are experiencing. These sensors will all be linked to the base stations.

In addition, there have been applications of machine learning in the agriculture sector, such as research on plant diseases and pests and other related topics. The challenge of accurately diagnosing plant diseases has been tackled using a variety of different machine learning strategies that have seen widespread use. In (Potato leaf diseases detection and classification system [8]), a Neural Network-based approach is suggested for evaluating potato health using leaf image datasets.

In addition, the experimental study described in (Application of neural networks to image recognition of plant diseases [9]) was carried out, the primary objective of which was to develop an imaging-based diagnosis system for plant diseases. Four distinct kinds of neural networks were trained based on shape, color, and texture variables collected from a disease picture dataset. The findings demonstrated that a neural network that is based on image processing may boost the accuracy of identifying plant diseases.

Image processing technologies might also be used to identify the scab disease that affects potatoes (Scab diseases detection of potato using image processing [10]). This is an added benefit. To begin, photographs taken at a variety of potato farms were gathered. Following the completion of image enhancement, picture segmentation was carried out in order to obtain the target area. In the end, a histogram-based method of analyzing the target area was used so that the phase of the illness could be determined.

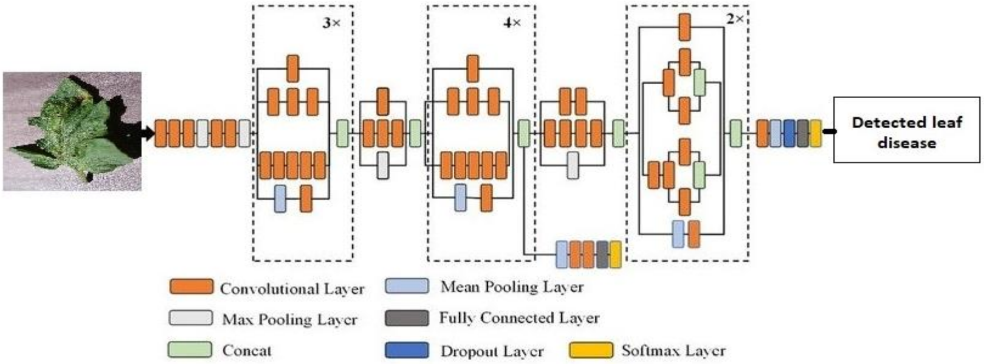

Figure 1: Model Diagram

3. METODOLOGY

In the proposed methodology, the main aspect is to identify the illness of tomato leafs. Here we have taken an image dataset from Kaggle where it contains 10 thousand of images which have been used for training the model. Convolutional Neural Networks a deep learning model is used here to train the model. Training is carried out with the help of the Inception-V3 model shown in figure-1, where it is the popular model having 164 layers deeper network and can classify images into 1000 categories. Model has been created with dataset partitioned in to Training set, validation set and Test dataset. Model has been trained to identify the leaf diseases of tomato. Model is well trained and generating a good accuracy in predicting the leaf diseases on which it is trained. CNN is the popular algorithm for image analysis in deep learning, so we have chosen this algorithm to implement this model. A technique for evaluating the health of plants using leaf image datasets is presented here. This approach is based on a neural network. In its latest iteration, Inception V3, a Convolutional Neural Network (CNN) lays the foundation for Inception's advanced artificial intelligence capabilities. This design comprises various elements, including convolutional layers, pooling layers, and fully-connected layers. The convolutional layers play a vital role in extracting features from the input image, while the pooling layers work to condense data by grouping closely situated data points into singular units. The architecture incorporates both convolutional and pooling components within its fully-connected layers to formulate predictions.

To prevent the issue of overfitting, Inception V3 integrates batch normalization layers and dropout layers into its structure. Moreover, an experimental study was conducted with the objective of devising a methodology for detecting plant diseases through photographic analysis.

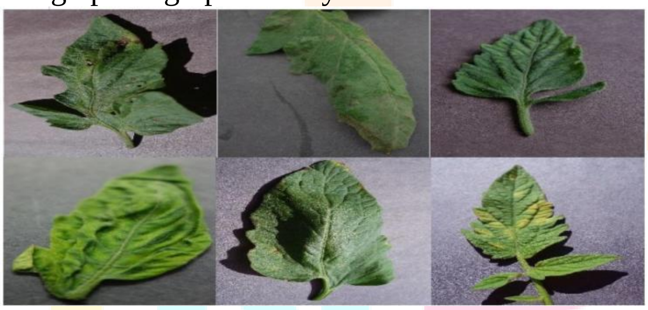

Figure 2: Sample Input Image

4. RESULTS

This paper utilizes CNN model known as Inception V3 to classify images. The architecture encompasses a total of 48 layers, featuring components like pooling layers, convolutional layers, inception modules and fully connected layers. The Inception V3 model comprises five distinctive levels, starting with the Input Layer as the initial stage, responsible for accepting image inputs.

In the second layer, Convolutional Layers are employed to generate feature mappings from the input images, using filters to identify patterns within the images. The subsequent layer, known as Pooling Layers, serves to decrease the parameter count by progressively reducing the spatial dimensions of the image, resulting in more compact feature maps.

Following that, the task of classifying feature maps is taken up by Fully Connected Layers. The fifth layer is comprised of Inception Modules, which employ a combination of 5×5, 3×3, and 1×1 convolution filters. This strategic combination aids in diminishing parameter count while enhancing the model's performance. The final dense layer consists of 10 nodes, featuring a SoftMax activation function. The model is trained for 50 epochs using sample tomato leaf images depicted in Figure 2. at every iteration loss $\boldsymbol{L}$ is calculated by comparing the predicted aspect labels with the ground-truth labels using the cross-entropy loss function. The loss can be calculated as follows [38]:

$$L = -\sum_{i=1}^{n} y^{i} \log(f(X^{i}))$$

Where n is the number of examples in the source data, y^i is the ground-truth aspect tag for the i^{th} example, and $f(X^i)$ is the predicted aspect tag for the i^{th} example. Next, the computation of the gradients of the loss function with respect to the model parameters can be expressed as follows:

$$\nabla\theta L = \frac{\partial L}{\partial \theta}$$

Then backpropagate the aspect loss L_{as} and update the parameters of f_s. Back-propagate the gradients through the layers of the model to update the model parameters(θ):

$$\theta\_new = \theta - \alpha * \nabla\theta L$$

Here, α represents the learning rate, which determines the step size for parameter updates during optimization. Here we calculate train and validation accuracy by using formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

The formula of the Accuracy considers the sum of True Positive and True Negative elements at the numerator and the sum of all the entries of the confusion matrix at the denominator. True Positives and True Negatives are the elements correctly classified by the model and they are on the main diagonal of the confusion matrix, while the denominator also considers all the elements out of the main diagonal that have been incorrectly classified by the model.

The training data yielded a training accuracy of 95%, while the validation accuracy reached 81.9%, as demonstrated in Figure 3(a). The progression of validation loss is depicted in Figure 3(b). The paper also illustrates the prediction of leaf disease for a given input image, showcased in Figure 4.

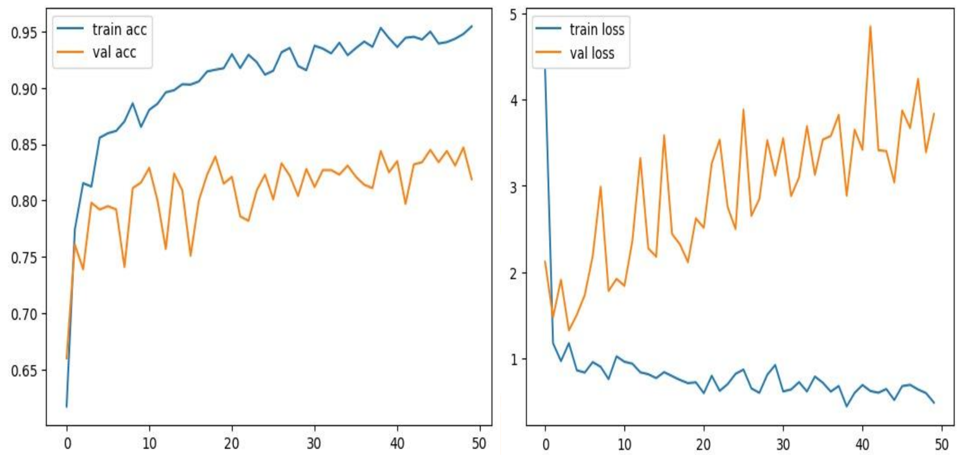

Figure 3: a) Graph Represents Train and Val Accuracy b) Graph Represents Train And Val Loss

Predicted class : Tomato___Tomato_Yellow_Leaf_Curl_Virus

Figure 4: Predicting leaf disease

5. CONCLUSIONS:

In this piece of research, 10 distinct diseases were observed for tomato leaf. Deep learning and CNN technology are used in the construction of the Inception-V3 model. Experiments have shown that the model is capable of accurately identifying the dataset, with an overall identification accuracy of up to 81.9%. The

next phase in the study process is to collect additional photos of different crop types and diseases.
Make sure the model is optimized. As a result of the experiment described in this study, we can show that the Inception-V3 variety of mixed network has successfully taken advantage of the related benefit. This model has reached a satisfactory level of recognition accuracy and should be subjected to more research and development. At the same time, we need to develop a network model that is capable of crop picture classification with a better degree of precision.

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