Original Article

Cloud Computing Based Advance System For Detection Of Plant Health

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Abstract

It is common for farmers to detect infections by speaking with regional specialists and conducting further experiments. Farming illnesses that eventually kill crops can impede crop growth. Due to the widespread spread of new diseases, farmers can have trouble understanding what's happening when things stabilize. In addition to affecting the nation's economy, agricultural diseases are crucial to controlling. Agricultural losses in India are 22.13% annually. Machine learning and the cloud can be used to identify diseases automatically to halt further crop losses. Even though a machine learning model is available for this proposal, it is not particularly advanced, reliable, portable, or practical in many ways. The user interface of the website allows farmers to upload a photo of a leaf to a cloud-hosted website to see how the disease has affected their crops. With the help of real-time data generated from 7,000 leaf photos, Convolutional Neural Networks (CNN), MobileNet, and machine learning libraries such as TensorFlow and OpenCV, it is possible to identify plant diseases with an average accuracy of 98.12%.

Keywords : Crop Disease, Machine learning, Convolutional Neural Network, Agricultural losses, Leaf photo

I. INTRODUCTION

India's expanding population has put us in a situation where we urgently need food. Farmers grow 60% of the annual agricultural production in India, excluding exports. In India, there are 54.6% farmers overall, of whom 70% reside in rural areas and make up roughly 60% of all farmers [1]. Agriculture is a significant business in India, as it still occupies roughly 60.43 percent of the nation's land. Crop losses range between 15% to 25% a year, with losses on crops valued close to 500 crore. By contacting local authorities, adhering to their recommendations, and conducting some testing, farmers can prevent catching these diseases [2]. Due to the rapid spread of new illnesses and climate circumstances, it is never easy for farmers to recognise oncoming hazards. By uploading pictures of disease-carrying plants to a website created and saved via the cloud, which has a data set of diseased leaves and leaves, a cloud-based deep learning and plant monitoring system allows farmers to quickly predict diseases [3]. conceive of crop disease prevention strategies that farmers can use. Figure 1 represents the normal image and diseased image [4]. There was an earlier machine learning model for this proposal, but it lacked sophistication, dependability, portability, and usefulness in different ways. It is also challenging for others to use the results in real-time applications [5].

Figure 1: a) Normal Leaf b) Diseased Leaf

Results are more accurate when MobileNet, machine, and deep learning architecture libraries are used effectively. TensorFlow is a machine learning and artificial intelligence software library that is open source and free [6]. Although it can be used for a variety of other tasks, its primary field of study is the training and inference of deep neural networks. The computer vision and image processing programme OpenCV is quite helpful [7]. It is a free library that may be used for a variety of tasks, including face recognition, object tracking, landmark recognition, and more. Amazon Web Services offers a variety of services, including cloud computing [8], servers, networking, and security (AWS). A straightforward HTML website with a user interface can be used by farmers.

II. RELATED WORK

The data augmentation strategy was used to increase the number of training datasets on the original training dataset, making the models learn more efficiently. The researchers tested the performance of these six models to find out which was most effective in predicting disease severity in citrus trees. The Inception-v3 model produced the best classifier, which was 92.60%. Machine learning techniques have recently developed in the field of agriculture. Companies [9], governments [10] and academic institutions [11] are very interested in it. This section will discuss some of the research supporting the use of different machine learning methods for crop disease diagnosis.

As plant diseases have a significant negative impact on agricultural production worldwide, many scientific efforts have been made to improve crop surveillance and disease diagnosis. The authors of [12] investigated the use of deep learning algorithms to identify leaf disease markers in cassava. An image collection of 720 affected leaflets in an agricultural area of Tanzania was used to build the CNN model. Seven different diseases including brown stripe dwarf disease, leaf mosaic disease, green bug, red bug, brown spot and nutritional deficiency disease can be distinguished on cassava leaves through the pattern generated. When used to find cassava infections in actual photos, the created approach, however, has a low classification rate.

The early diagnosis of blast illness has been made possible by Chen and colleagues' use of Internet of Things (IoT) and artificial intelligence (AI) technology [13]. RiceTalk is a platform that was created for blast detection utilizing non-visual Internet of Things sensors that produce sensory data from field-grown crops. The CNN model can be automatically trained and evaluated in real time using the discovered data [14]. To detect rice blast in real farming situations, RiceTalk had an average prediction accuracy of 89.4%.

Another DL-based platform is suggested in [15] for the diagnosis of plant diseases and insect pests. In a manner similar to [16], researchers employed CNN as the fundamental DL tool to discover 27 agricultural illnesses in China's challenging hilly environment.Chinese farmers can easily use this system as it is created as a Java applet. The overall recognition accuracy is 86.1%, as shown by the study results of the authors. According to the CNN model (R-CNN) based on the masked region [17], Jiang et al. [18] proposed methods to detect diseases on apple leaves. The DL model called R-CNN for Version Object Segmentation can find objects of interest in an image and provide a segmentation mask for each instance. The dataset was used to train the CNN network to recognize the most common diseases in apple trees, using photos of infected apple leaves (2,029 total).The model created can identify five diseases: rust, brown spot, leaf mosaic, gray spot, and alternaria leaf spot. With a fairly little training dataset, the generated CNN model has a classification accuracy of 78.8%.

III. PROPOSED SYSTEM

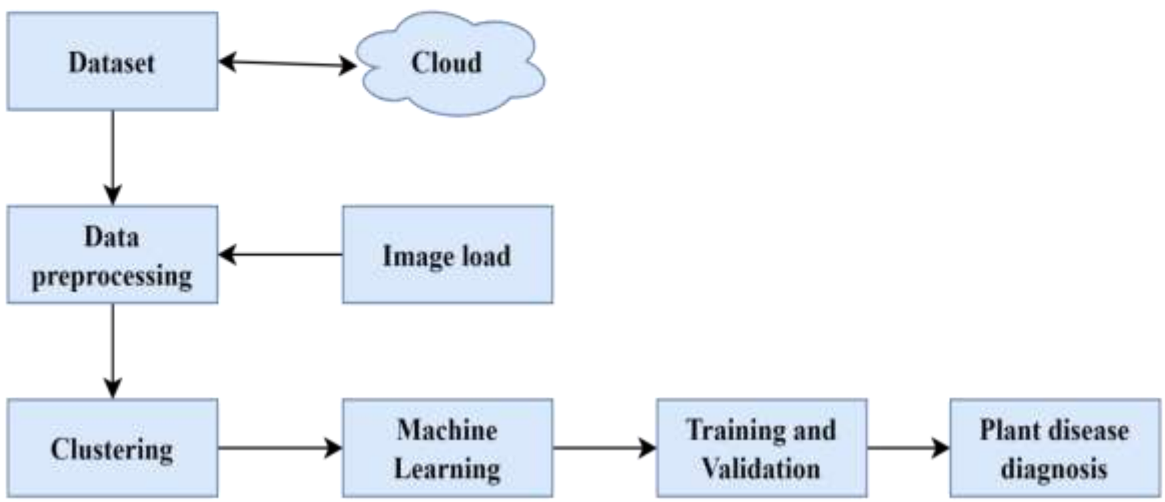

Figure 2 : Plant Health Detection System

Figure 2 shows a cloud-based method for plant health detection. The aim of the proposal is to identify and treat plant diseases, as this is an important issue that deserves special attention. To improve the performance of the proposed model, several issues need to be identified. The major goal of the proposal is to determine how to make the system portable and accessible to all users. Testing various input and output results, framing algorithms for accuracy, using mathematical calculations, and hosting cloud web sites are all crucial for designing proposals in the best and most effective ways possible. In order to implement this concept, a model must be created that can identify pictures of leaves and provide various outputs in response to various inputs. The disease form must be filled out completely and submitted together with any pertinent information, including details on the condition, its prevention, and symptoms. By uploading a picture of a healthy leaf, it will also display the condition of the tree. Models are required to disclose whether or not a second photo they post is actually a photograph. The models' two datasets one for training (30%) and one for testing (70% were partitioned at random into sets of leaf images.

Training, validation, and testing are the three segments in our dataset. Image quality was used in three stages for 38 diseases in 14 plant species. The structure of the CNN model and the adjusted hyperparameters are used to calculate the number of frames in each phase. Through a series of carefully monitored experiments, we estimated hyperparameters to improve prediction performance and accuracy. It tested many times different combinations of hyperparameter values until we got the desired result as shown in Figure 3. Cross-validation optimizer was also applied to find the set of hyperparameters. Optimal. To increase the training accuracy and reduce the training loss of the CNN model, several image preprocessing adjustments were made to the training dataset. Specifically, we changed the color contrast of the image, added Gaussian noise, and used image desaturation, which reduces the color saturation of pixels by increasing the black-to-white ratio. These changes are mainly made to reduce the impact of the background. Part of the training process. This improved the stability of our CNN model and improved our ability to learn all 38 disease classifications.

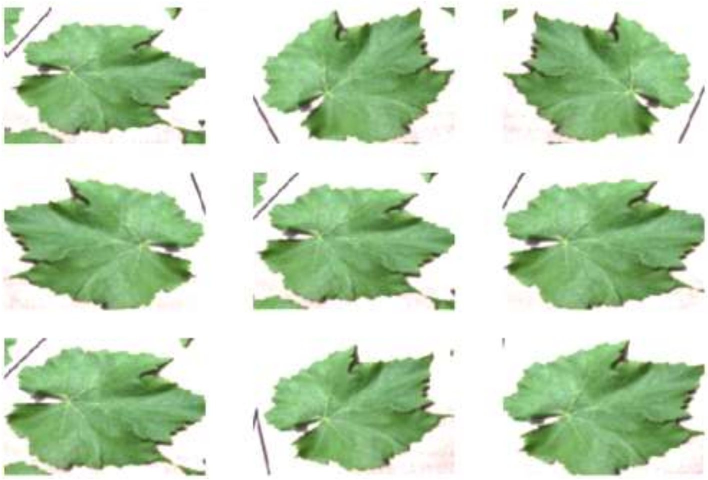

Figure 3 : Dataset Augmentation

IV. RESULT AND DISCUSSION

In most cases, only healthy data (positive samples) and each plant disease or pest sample must be identified manually by visual inspection. Much of the learning-based techniques currently used to identify plant diseases and pests are based on supervised learning using a large sample of diseases and pests, which requires further research. on unsupervised learning. It takes a lot of work to collect labeled records manually. These illustrate the accuracy and loss of training a dataset in figures 4 and 5. When the model trains the dataset, the accuracy and loss are plotted on the Y-axis, while the epoch is plotted on the X-axis.

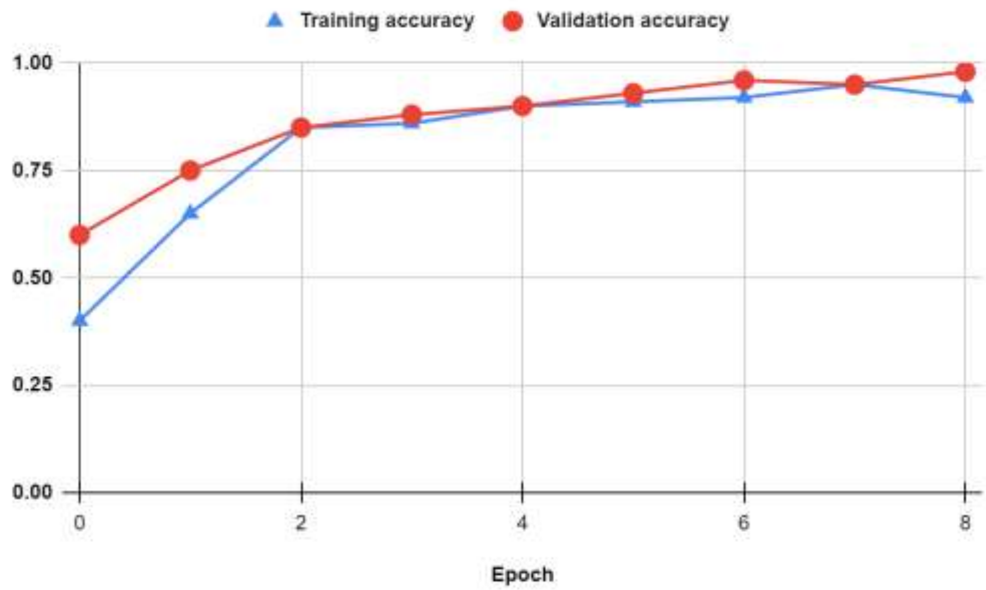

Figure 4 : Accuracy vs Epoch

By using this approach, it can determine which disease is causing the plant to fail. It explains how to prevent plant diseases on any device, including a computer or mobile phone. It is expected to take an approximation of the image, of which 70% is the image and the remaining 30% is the test image. Each image in the training set is classified as either benign or malignant. The output of each rendered image is benign or malignant based on its accuracy. The example shows how this method uses a learning method to identify and classify images. This gives a total accuracy of 98.12%. The diagnosis of the plant's health is shown in Figure 6. Figure 7 depicts the diagnosis of healthy and diseased leaves.

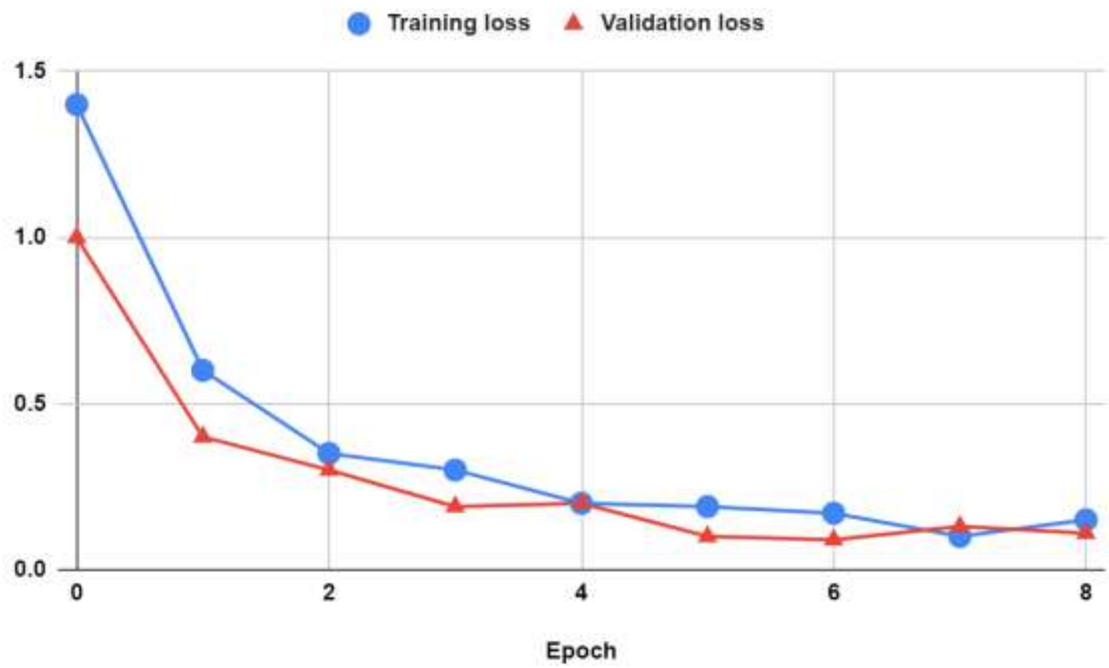

Figure 5 : Training and Validation Loss vs Epoch

Figure 6 : Plant Health Diagnosis

Figure 7 : Healthy and Diseased leaf diagnosis

V. CONCLUSION

The prevalence of agricultural illnesses must be decreased by action. Convolutional neural networks and neural network operations learning techniques were utilized to demonstrate a cloud-based deep learning and factory monitoring system. It created, checked, and tested the model using the plant dataset. In images obtained in some of the epidemic-affected states, this pattern is clearly visible. In order to select the base model, it performed tests on metrics like accuracy, precision, and memory. It ultimately settled on the MobileNet V2 format, which has the highest accuracy ratings at 98.12%. Model presentation for deployed frameworks is made simpler by MobileNet's mathematical performance. By creating the proposal, it learns more about agricultural diseases, how they affect farmers, and others.

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