EDGE AI BASED PLANT DISEASE DETECTION SYSTEM

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Abstract: Agriculture is a crucial industry to humankind's continued existence. Simultaneously, digitalization's pervasive influence made it simpler to accomplish previously challenging jobs in a wide range of disciplines. The agriculture industry, for both the farmer and the consumer, would greatly benefit from technological and digital adaptation. Through the use of technology and consistent monitoring, illnesses can be detected early on and removed, resulting in a higher yield. The economic, social, and political lives of farmers and the entire agricultural industry are profoundly impacted by the health and productivity of their crops. Therefore, in order to detect the illnesses at the proper moment, it is essential to conduct careful monitoring at different phases of crop growth. However, humans may require more than their natural attire, and there may be situations when doing so would be deceiving. Accurate identification requires a system that can automatically recognise and categorise the numerous illnesses that can affect a given crop. The current proposed framework was inspired by this train of thought. The suggested framework is primarily concerned with the transfer learning phenomena based on VGG16, and the "Plant Village" dataset, which contains both damaged and healthy potato and tomato leaves, is being explored for implementation.
Keywords: Transfer learning, VGG16, Plant Village.

INTRODUCTION

When thinking about the economy of India or other developing countries, agriculture is an essential sector. It stresses the significance of attentive plant care from germination to harvest. Weather conditions, crop survival against numerous illnesses, and animal survival are just a few of the many challenges the crop faces along the way to fruition. The issue can be remedied if the field is adequately protected so that the crops are not damaged by the numerous animals during these crucial times. The second major issue is the weather, which is not under human control and can only be hoped for in order to produce better crops. Preventing the spread of diseases that could stunt the crop's development and reduce its yield is the top priority. If these diseases are caught in time, the crop can be protected using the correct fertilisers. The agricultural community would benefit greatly from a digitalized disease identification and classification system. This will shorten the time it takes to identify diseases and improve the accuracy of disease classification.

There have been several efforts made to reduce disease-related crop failures. Over the past decade, IPM strategies have gradually supplanted conventional approaches to pest control through the use of fewer and less toxic insecticides. The first step in efficient disease management, regardless of approach, is correct diagnosis at the earliest possible stage. Historically, organisations like plant clinics and agricultural extension offices have helped find and name diseases. Recently, the advent of online resources for illness identification has aided these activities by capitalising on the worldwide increase in Internet usage. Recent years have also seen the development of mobile phone-based tools, which have benefited from the remarkable global usage of mobile phone technology.

LITERATURE SURVEY

On Using Transfer Learning For Plant Disease Detection by Abhinav Sagar and Dheeba Jacob.

In this research, the authors demonstrate the utility of deep neural networks for image-based disease detection in plants. They used the Plant Village dataset, which is available for anybody to use and includes 38 different types of diseases. Ours is, therefore, a multi-class categorization problem. ResNet50, which employs connection skipping with a residual layer, archived the best result on the test set out of the five architectures they studied (VGG16, ResNet50, InceptionV3, InceptionResNet, and DenseNet169). Accuracy, precision, recall, F1 score, and the class confusion metric were utilised to evaluate the outcomes. With ResNet50, the model's accuracy is at its highest, reaching 0.982, the recall is at 94 percent, and the F1 score is at 94 percent.

Disease detection in rice leaves using transfer learning techniques by Gugan Kathiresan1, M Anirudh1, M Nagharjun1 and R Karthik.

In order to achieve statistical parity across the illness samples, this research makes use of a generative adversarial network. In addition, they examine the model in relation to competing transfer learning frameworks. The provided model, when put to the test on a GAN-enhanced dataset, outperforms standard classification architectures with an average cross-validation accuracy of 98.79%. Three datasets are used to compare the model without the GAN enhancement.

PLANT DISEASE DETECTION USING VGG AND DJANGO by Jyothirmai Sai Sri Gelli1, Lakshmi Akhila Madduri2, Roshan Tanveer3, Udaya Bhanu4, G Krishna Kishore5

Using image processing techniques, the automatic disease detection system can automatically detect and identify unhealthy parts of leaf images and classify plant leaf disease. They use this training data to train the data and then anticipate the output with maximum accuracy. This is done by collecting a subset of the leaves and then training those leaves. Because they utilised the Django framework. Now, the uploaded image is analysed for patterns and compared to a data collection that yields virtually accurate findings in identifying plant diseases. The disease's early stages allow for simple diagnosis. Farmers' time and energy spent keeping tabs on massive farms and the diseases they harbour is lightened by the proposed concept. Assessing Efficiency

Problem statement

In order to accurately predict the onset of leaf disease in tomato plants, our team has developed a system using transfer learning VGG16, a Convolution Neural Network.

Methodology

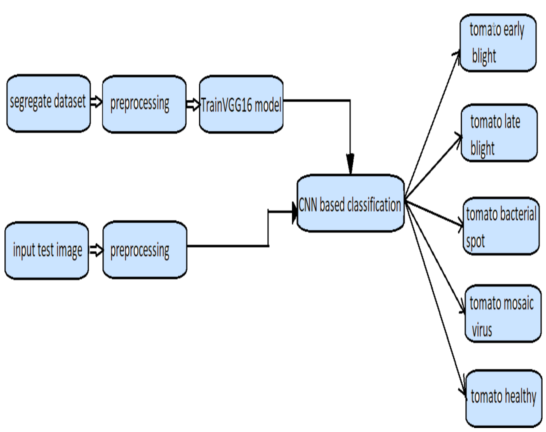

Figure.1: Block Diagram

The first step is to amass the dataset and divide it into a training set and a test set, with 5 separate folders for each ailment. The photos in the dataset are then preprocessed so that the model may be trained with minimal effort. In preprocessing, you can do things like resize, rotate, flip, etc. The next crucial step is to construct the VGG16 model and then train it using the training dataset. Model is then tested on either the training set or on unseen data.

Dataset have 5 categories of images

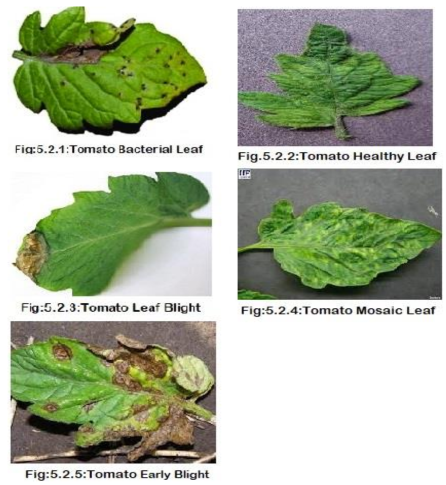

Figure. 2: Five Categories of tomato plant leaves.

Implementation

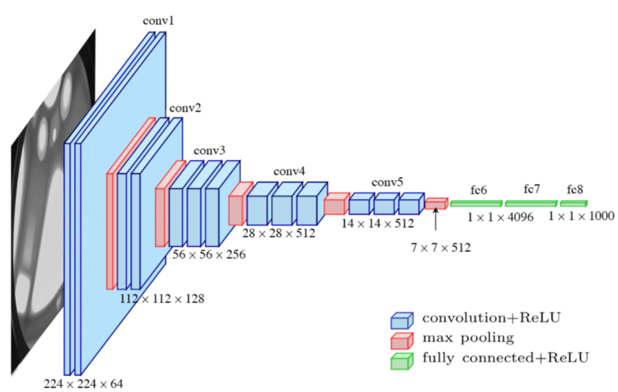

Figure. 3 : VGG16 Architecture.

The 16 in VGG16 indicates that there are 16 weighted layers. While VGG16 contains a total of 21 layers—13 convolution layers, 5 Max Pooling layers, and 3 Dense layers—it only has 16 weight layers, or layers with tunable parameters, to train with. VGG16 accepts 224244 input tensors with three RGB channels. Instead of using a large number of hyper-parameters, the VGG16 model relies on convolution layers of 3x3 filters with stride 1 and the same padding and maxpool layers of 2x2 filters with stride 2. Every part of the structure follows the same layout for the convolution and max pool layers. The number of filters in Conv-1 is 64, in Conv-2 it's 128, in Conv-3 it's 256, and in Convs 4 and 5, it's 512. After the stack of convolutional layers, we have three Fully-

Connected (FC) layers, with a total of 4096 channels (2 x 4096). The third FC layer is responsible for classification and has a separate channel for each class. The soft-max layer follows as the last one.

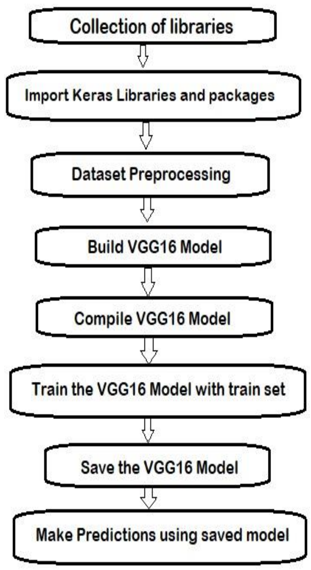

Figure.4: Implementation steps.

Figure shows the implementation step of the system.

Results and Snapshots

- System accuracy on 30 epochs.

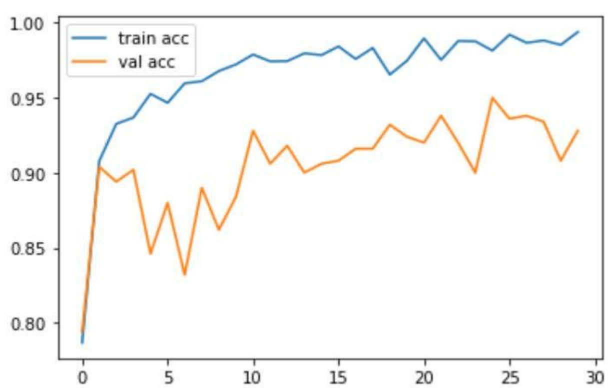

Figure.5: Accuracy graph.

The graph shows the accuracy of the system on 30 epochs , and at 30th epoch the system got the accuracy of 92.80%.

Result Snapshot

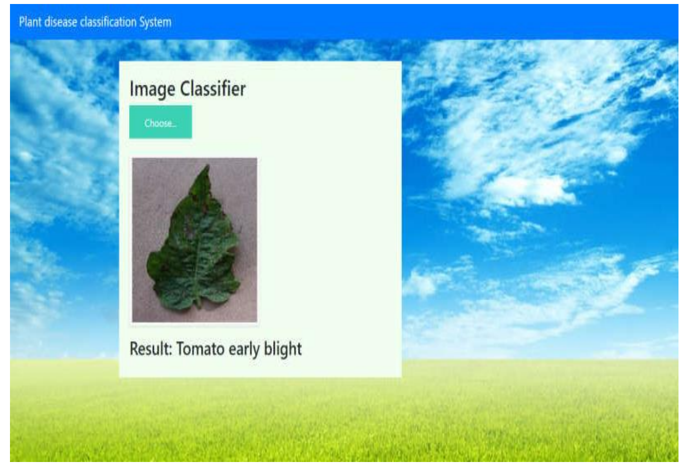

Figure.6: Prediction for the given image.

Figure shows the output of the system on giving Tomato early blight image to the user interface. And the system gives the right prediction.

References

[1].On Using Transfer Learning For Plant Disease Detection by Abhinav Sagar and Dheeba Jacob.

[2].Disease detection in rice leaves using transfer learning techniques by Gugan Kathiresan1, M Anirudh1, M Nagharjun1 and R Karthik.

[3].PLANT DISEASE DETECTION USING VGG AND DJANGO by Jyothirmai Sai Sri Gelli1, Lakshmi Akhila Madduri2, Roshan Tanveer3, Udaya Bhanu4, G Krishna Kishore5.

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