ORGANIC PRODUCT DISEASE DETECTION USING CNN

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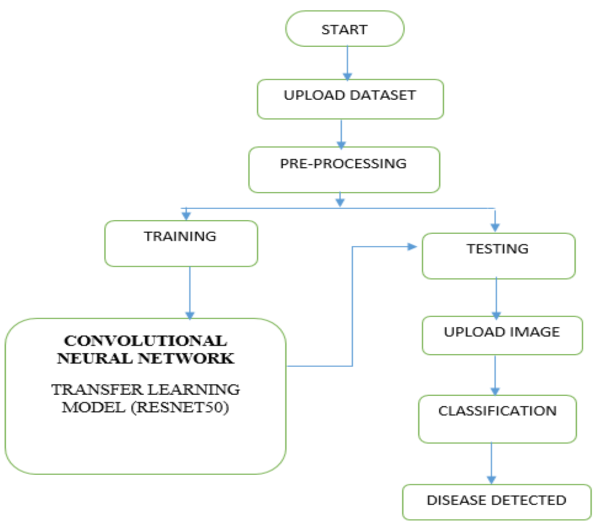
Abstract – Because agriculture is vital to the economy, plant diseases must be kept to a minimum. Early problem detection is crucial, but manual inspections take a long time, are labour-intensive, and are prone to mistakes. Fruit colour, shape, or texture data can be extracted using artificial intelligence to help find diseases. Convolutional neural network (CNN) approaches have recently demonstrated outstanding results for image categorization problems. Large datasets can be processed quickly by CNN, which extracts more precise characteristics. In this study, we classified fruits and their diseases using a mixed deep neural network and contour feature-based technique.

1. INTRODUCTION

Early plant disease diagnosis is economically crucial. Modern computer vision and machine learning technologies may detect and characterise diseases at an extremely early stage, hence limiting illness transmission and improving cure rates. When sickness symptoms first appear, it may be too late to take meaningful action, but in other A Creative Commons Attribution 4.0 International License has been applied to this work, allowing for its free use, distribution, and reproduction in any format as long as the original work is properly attributed. In this paper, three fruits—grapes, mango, and banana—have been studied. It is now possible to control black rot using a mix of good cultural techniques, fungicides, and resistant cultivars. The first indication of black rot is a black border forming around the edge of leaves.

2. OVERVIEW



3. LITARATURE REVIEW

[1] Fruit Grading and Disease Detection in Image Processing for Smart Farming Authors (Rushikesh Borse, Ashwani Kumar, and Monica Jhuria), 2013:

Improved fruit production is vital because agricultural companies need large yields; to do this, automated techniques that can detect fruit disease are needed. For this, an artificial neural network methodology that can classify fruit infection is suggested. K-Means clustering is used to locate unhealthy fruit areas, although it has the drawback of a significant estimate load. It will motivate agronomists to improve production and exercise sound judgement from time to time.

[2] Manisha A. Bhange and Prof. H. A. Hingoliwala, authors, A Review of Image Processing for Pomegranate Disease Detection 2015:

The procedure offers a suggestion for how to identify pomegranate fruit disease. In this procedure, a web-based technique is used to assist non-experts in diagnosing fruit diseases based on a photograph of the fruit's symptoms. Farmers are able to photograph fruit diseases and transmit the images to the system. Farmers would then be able to determine if the fruit has been impacted by bacterial blight or not.

[3]Using image processing to grade tomato maturity at a low cost for farmers, Sudhir Rao Rupangadi, Ranjani B.S., Prathik Nagaraj, and Varsha G. Bhat, 2014:

Fruit ripeness is categorised using this technique depending on its color or texture. It uses modern approaches, primarily manual inspection, which results in inaccurate classification and causes financial losses owing to subpar produce throughout the supply chain. The drawbacks are a number of approaches that demand expensive setups and labor-intensive processes; total accuracy is up to 98%.

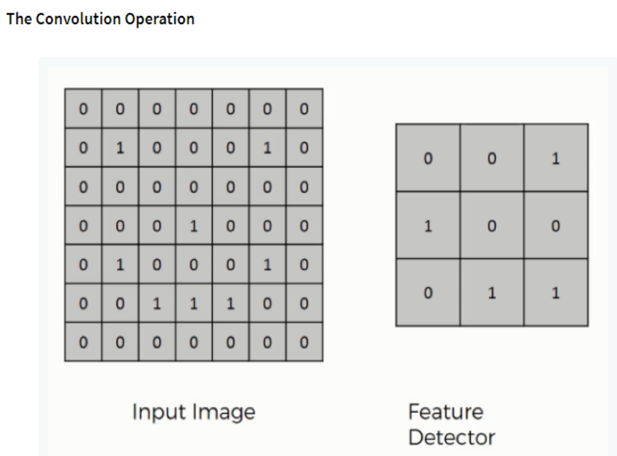
4. METHODOLOGY AND ALGORITHMS

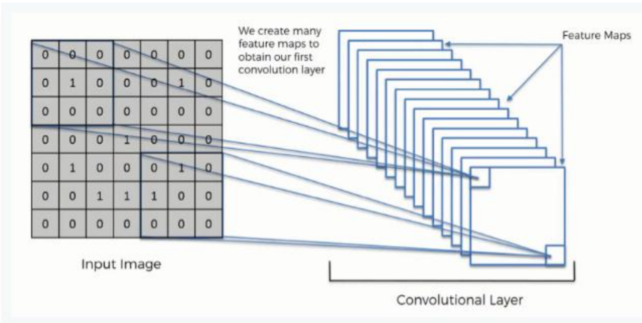
In this study, basically four algorithms are applied. They are the deep neural network, pertained deep learning model, Resnet50, deep neural network, and convolutional neural network. Each of these elements is essential for spotting plant diseases in a unique way.

Convolutional neural network

Step1: convolutional operation

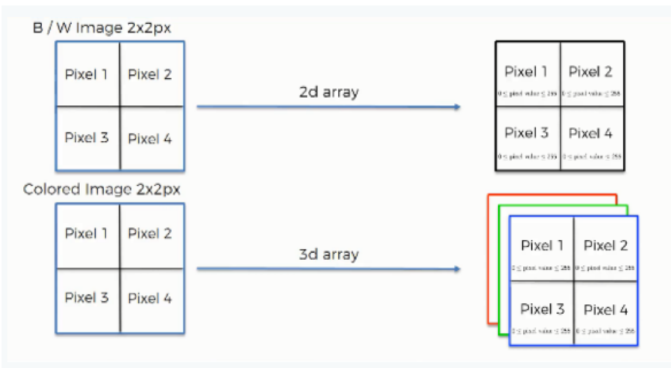
The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.





Step (1b): Relu Layer

The second part of this step will involve the Rectified Linear Unit or Relook. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks.



Not necessary for understanding CNNs, but there's no harm in a quick lesson to improve your skills.

Step 2: Pooling Layer

We'll discuss pooling in thi

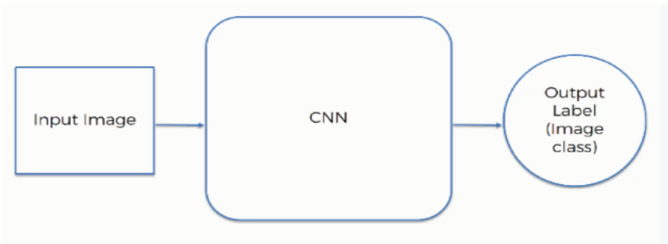
s section and learn exactly how it typically operates. But max pooling will be the central concept in this situation. However, we'll discuss a variety of strategies, including mean (or total) pooling. This section will conclude with an interactive visual example that will undoubtedly clarify the entire idea for you.

Step 3: Flattening

Here is a basic explanation of the flattening procedure for convolutional neural networks, including how to switch from pooling to flattened layers.

Step 4: Full Connection

We will combine what we discussed in the previous section in this section. By understanding this, you'll be able to visualize Convolutional Neural Networks more clearly and understand how the "neurons" they produce ultimately learn to classify images.



5. PROPOSED SYSTEM

We are incorporating deep learning ideas into the suggested system. Here, in order to categories' fruits and their ailments, we merged deep neural networks with a feature-based contour technique. Using pertained ResNet50 models to extract deep features, a method for classifying. plant diseases was suggested.

Advantages:

- Cheaper to operate.
- It can be scaled up quickly.
- Time minimising.

3. CONCLUSIONS

Using training data from 6509 photos of rice leaves and testing data from 2000 distinct images, we have suggested a deep learning architecture in this research that accurately classifies 99.6% of the test images. The performance of the model, which had previously not produced adequate results on such a tiny dataset, has been considerably enhanced by transfer learning utilising fine-tuning the default ResNet50. Because we had a cut point after which the accuracy was not advancing and the loss was not lowering on both the training and validation data, the number of epochs used was terminated at 25.

REFERENCES

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[2] A Cost-Efficient Tomato Maturity Grading System Using Image Processing for 974 2015 International Conference on Green Computing and Internet of Things (ICGCIoT) Farmers, International Conference on Contemporary Computing and Information, 2014.

[3] Manuel Toledano,Enrique Rico-Garcia, Rafael A. BorquezLópez, Abraham Gastélum-Barrios Ayala and Genaro M. Soto-Zaraza, "Tomato Quality Evaluation using Image Processing: A Review," African Journal of Agricultural Research, Vol. 6(14), July 18, 2011, pp. 3333–3339.

[4] "Image Processing and Machine Learning for Automated Fruit Grading System: A Technical Review" by Rashmi Pandey, Sapan Naik, and Roma Marfatia Volume 81, Issue 16, November 2013, International Journal of Computer Applications (0975 - 8887)

[5] Swapnil Kumar Sharma, Anshuka Srivastava Creating a Robotic Navigator to Help Farmers in the Field Proceedings of the 2010 IMECS (International Multi Conference of Engineers and Computer Scientists), held in Hong Kong from March 17–19.

[6] "Image Processing and Machine Learning for Automated Fruit Grading System: A Technical Review" by Rashmi Pandey, Sapan Naik, and Roma Marfatia Volume 81, Issue 16, November 2013, International Journal of Computer Applications (0975 - 8887)