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Fruit Disease Identification and Categorization Using Deep Learning

N. Venkata Ravi Kumar
Computer Science and Engineering(Data Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
ravik.48149@gmail.com

S. Manikanth Reddy
Computer Science and Engineering(Data Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
siriganagari143@gmail.com

J. Gowtham Reddy
Computer Science and Engineering (Data Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad, India
rsai87822@gmail.com

Swathi Sugur
Assistant Professor
Computer Science and Engineering(Data Science)
Sphoorthy Engineering College (JNTUH)
Hyderabad,India
swathi.tekumal@gmail.com

Abstract

Agriculture has a substantial role in the Indian economy within the context of India. This is the primary and essential source of income for a significant portion of the human population. Therefore, it is important to enhance the output of fruits. Fruit diseases have a negative impact on the quality and overall condition of fruits. The primary cause of fruit illnesses is mostly attributed to fungal and bacterial pathogens. The timely identification of fruit diseases serves as a means to forecast and mitigate the occurrence of such diseases, hence resulting in cost savings for agricultural practitioners. The identification of an optimal approach for fruit disease detection is used as a proactive measure to mitigate the impact of fruit diseases during their first phases. Certain researchers have undertaken the task of developing a fruit disease identification system with the aim of safeguarding farmers' investments. The primary aim of this study is to conduct a comparative analysis of a deep learning classification approach in the context of fruit disease detection. This research we proposed an fruit disease detection and classification using hybrid machine learning and deep learning techniques. The various feature extraction and selection technique are utilized and ML and DL classification algorithms are applied on heterogeneous fruit dataset. In extensive experimental analysis the proposed hybrid Resnet achieves highest 96.10accuracy for all fruit image dataset.

Keywords: Fruit Disease Detection, Feature extraction, Feature selection, Papaya fruit, Deep Learning Techniques, Classification

Introduction

Detecting fruit diseases is an area of study. It lays forth novel approaches to automatically detecting fruit diseases. Identifying citrus fruit diseases is our primary goal in developing this model. The raw material from citrus trees is used in the agricultural sector to make a variety of agriproducts, and the plants themselves are associated with several health advantages. Diseases such as blackspot, cankers, scabs, greening, and melanose can affect citrus fruit trees. Citrus fruit diseases cause the annual rejection of a large quantity of natural products. As a result, there is a need for a mechanized framework for identifying citrus diseases since the process of distinguishing proof of infections has traditionally been carried out by humans, which is error-prone, tedious, and expensive. Consequently, effective identification of citrus diseases helps us reduce losses and improves product quality. It is now much easier to filter and detect irregularities in a harvest continually, thanks to advancements in current gadgets and rapid PC assisted tactics. Additionally, encouraging results in horticulture have been achieved with the use of deep learning procedures, which have helped more ranchers and food-creating workers with tasks such as controlling picture inspection, locating plant infections, investigating weeds, and revealing crucial seeds. A small number of other operations are focused

on anticipating future limits, such as yield generation, environmental factors, and field soil water content. Considering the outcomes of Convolutional neural network (CNN) based approaches to picture clustering, we provide a deep learning model for automated fruit illness detection.
Agriculture has an essential role in the economic growth and general advancement of countries throughout [1]. There are a lot of big obstacles that have to be overcome all the time in the transportation of agricultural goods around the globe. Modern farmers may become more efficient, productive, and profitable by gaining access to decision-making tools and technological advancements that can help them integrate their commodities, skills, and services more smoothly [2]. Maybe this phrase sums up the idea of "smart farming" well. The goal of increasing fruit yield is to boost the agricultural economy by increasing the total amount of fruit output. There is no more important industry than agriculture when it comes to driving growth in the economy, creating jobs, and facilitating trade between countries.

LITERATURE SURVEY

The writer's examination took into account and evaluated the following infections: Anand, Shiv Dubey, Apple Smear, Apple Rot, and Apple Scab [1]. As part of the picture pre-handling process, read the input image and convert it from RGB to L*a*b* shading space. Worldwide Shading Histogram and other similar elements are used for fruit disease sickness recognized evidence. Completed Neighborhood, Nearby Paired Example, and Shading Intelligibility Vector Twofold Example.

[2]. Monika Jhuria, Ashwani Kumar, and Rushikesh Borse Black rot and powdery mildew are two of the most common grape diseases. The two most common apple diseases are rot and scab. The inventor elucidated picture pre-handling approaches, which include feature extraction, following the image-obtaining strategy, which is the capture of digital photos. Elements are extracted using three particular vectors: morphology, surface, and color.
[3]. B. Uma Maheswari, M. Nikhitha, and S. Roopa Sri The degree of illness is another factor that would be used to rank the fruit in the proposed system. The TensorFlow platform is used to develop the scheme. Fruits including bananas, apples, and cherries have been considered for the next project.

[4]. Rathamani, P. KanjanaDevi,Recently, algorithms for grouping and dividing fruit images have been used to identify fruit diseases. The algorithm plot is evaluated using several evaluations to demonstrate its relevance.

[5]. Chetan Marwaha, Kawaljit Kaur,In this research, we take a look at the illnesses that might arise from harvesting fruits. The corruption of the fruit crop is broken down using image handling processes. There is a thorough introduction to the analysis of filtering processes associated with distortion recognition. Singh, Uday Pratap, and Chouhan, Siddharth Singh This study examines mango leaves for signs of Anthracnose disease infection and categorizes them accordingly. The categorization in the article was done using a convolutional neural network. Additionally, the most recent development pertains to the measurement of fruit based on its characteristics. [9]. Jianxin Wang, Yu Sun, and Guan Wang The seriousness of the plant disease is examined in this article. For this analysis, we considered two models: one that relies on transfer learning by calibrating the top layers of a preprepared deep network, and the other that builds a shallow network in the absence of preparation.

METHODOLOGY

In order to identify the fruit disease, many methods were used. Object identification and feature extraction are the first steps in the fruit disease detection method. Methods used to detect the fruit disease include the ones listed below.

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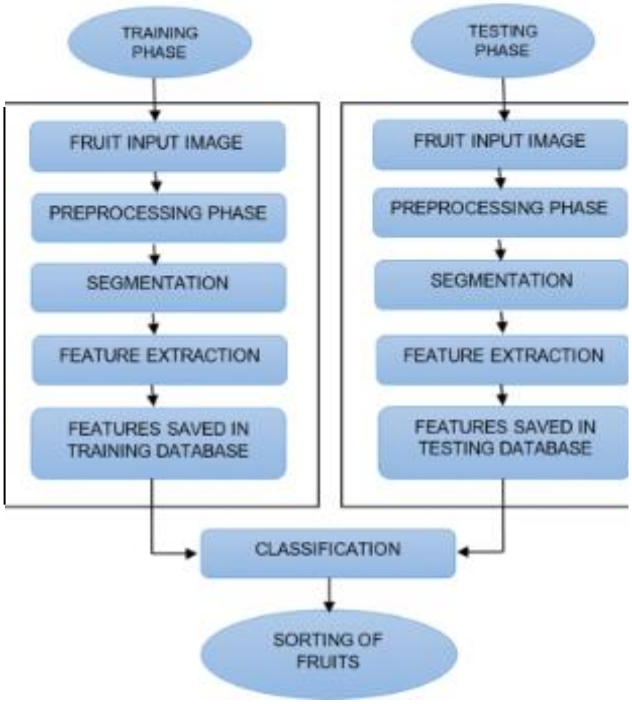

Module description

Image Acquisition:

The first stage of the system designed to detect fruit illnesses is the acquisition of photos. Most of the time, the quality of photographs captured by sensors, drones, or cameras is top-notch. In RGB format, the gathered images are stored. A device-independent hue conversion is implemented to the color conversion framework when the RGB fruit picture's color conversion framework is created.

Image Pre-processing:

To remove unwanted elements or background noise from an image, one might use one of many techniques. Cropping the fruit shot to get the important part of the image is the first step in photo editing. Any time smoothing is required, a smoothing filter is used. Picture processing begins with an enhancement to boost contrast, continues with color conversion to turn RGB images into grayscale, and culminates with histogram equalization to ensure that picture intensities are evenly distributed.

Image Segmentation:

What we call "segmentation" really involves dividing an image into smaller pieces that share certain commonalities or have comparable traits. In the segmentation process, several approaches may be used, including k-mean clustering, the otsu' method, and the transformation of RGB pictures into HIS models, among numerous others.

Feature Extraction:

Extracting Features is a technique that is utilized to assess the overall effectiveness and quality of an image by utilizing features such as color, surface texture, shape, and other similar characteristics. It is possible to extract features from a picture using a variety of methods, such as the Global Color Histogram, Color Coherence Vector, Local Binary Pattern (LBP)and Complete LBP.

Dataset

In this work, we used two types of datasets of various categories of fruits. One is the public dataset named FIDS-30, and the pictures of this dataset are collected from Internet sources. This open-source consists of 30 classes of fruits, as illustrated in Table 1. There are approximately 30 to 40 images in each category with a considerable variation of added noises. A significant contribution of this work is to present a dataset of various fruits images that we had obtained and captured by smartphone cameras. In this second dataset, we work with eight classes of fruits, which are primarily available in Bangladesh. As illustrated in Table 2, this custom dataset contains 761 images of apples, coconuts, grapes, limes, oranges, tomatoes, bananas, and guavas. demonstrates some sample images of the used open-source FIDS-30 dataset. Next, in the data splitting part, we assigned 80% of the images for the training, 10% for the testing part, and 10% for the validation part. Next, traditional data augmentation techniques, e.g., projection, rotation, scaling, changing brightness and contrast, etc., are applied to both datasets to enhance the efficiency of the deep learning technique.

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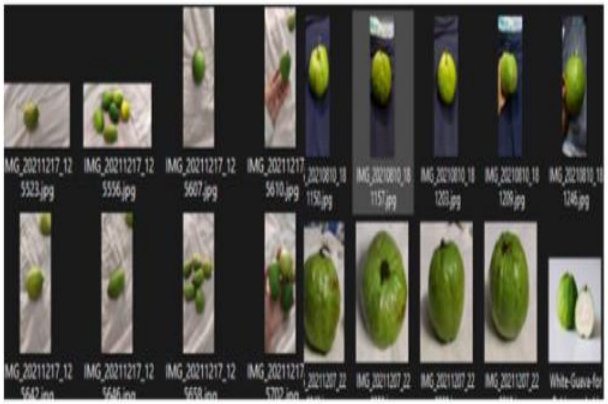

Fig1 : sample images

Model Description

This section describes the deep learning approaches that have been employed in this work for automatic fruit detection of multiple classes and classification of single category. In this paper, inceptionv3, Resnet, deep convolutional neural network framework has been used for fruit detection. The convolutional neural networks are a variation of profound networks, which consequently learn basic edge shapes from crude information and recognize the complicated conditions inside each picture through include extraction. The convolutional neural networks incorporate different layers compared to the human visual framework. Among them, the convolutional layers, by and large, have filters with the parts of 11×11, 9×9, 7×7, 5×5, or 3×3. The channel fits load through preparing and learning, while the loads can separate elements, only like camera channels.

ResNet

One deep learning model that has found usage in computer vision applications is ResNet. This design supports hundreds or thousands of convolutional layers, making it a Convolutional Neural Network (CNN). The performance of earlier CNN designs was severely constrained since they couldn't handle a high number of layers. Researchers ran into the "vanishing gradient" issue, however, when they added more layers.

Gradient descent is used in the backpropagation training of neural networks to identify the weights that minimize the loss function as it is shifted down. Overlapping layers cause the gradient to "disappear" due to repeated multiplications, and performance becomes worse as the number of layers increases. ResNet offers a novel approach to the "skip connections" problem—the vanishing gradient problem—and offers a solution. Instead of using the activations from the preceding layer, ResNet skips over the identity mappings (inactive convolutional layers) that are stacked on top of each other. Skipping reduces the number of layers in the network, which speeds up the initial training.

Web framework

In this work, the flask framework has been used to create a web application of the proposed fruit classification system. Python-based flask is an easy-to-use and flexible web framework [26]. This module is named a microframework because it does not require specialized instruments or libraries. It has no dataset deliberation layer, structure approval layer, or other parts where prior external libraries provide typical functions. However, this flexible module supports integrations that can add application features as if they were made inside of flask. Figure 7 illustrates how the proposed classification models have been deployed to a web and smartphone applications using the flask framework.

RESULTS

The proposed models' performance has been evaluated using the custom dataset obtained by the authors of the manuscript. The proposed inceptionv3 and ResNet convolutional neural networks have attained 96% and 66% accuracy, respectively, on the test data after the end of the tenth epoch. The confusion matrix in demonstrates how the models performed on the test dataset for eight classes of fruits. the behavior of training and validation accuracies concerning epoch numbers for the ResNet technique. According to, the training and validation losses of the inceptionv3 framework reduce significantly with the change of epochs. Interestingly, the results for the ResNet model for the custom dataset have not been reported, as the inceptionv3

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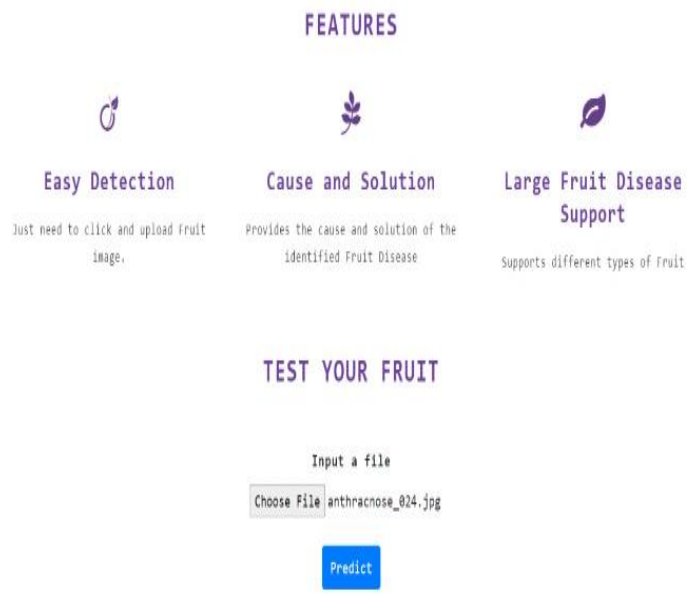
model performed slightly better than the inceptionv3 technique.

Algorithm	Accuracy
InceptionV3	66%
ResNet	96%

Home page



Prediction

Result of image

Conclusion

This work has developed an automated fruit classification and detection system using deep learning techniques. Two datasets have been utilized in this paper, i.e., an open-source FIDS-30 dataset of 30 classes and a custom private dataset of 8 categories of fruits. After applying the conventional augmentation techniques, the deep learning models are applied. The inception v3 approach is applied for the detection of multiple fruits in images. Inceptionv3 and ResNetmodels are employed for the automatic fruit classification. Finally, the deep learning models have been deployed into a website using the flask framework, API, and Android Studio. The proposed system is expected to use in industries and supermarkets and as an educational tool for children.

In the future, more advanced deep learning models with parameter tuning can be used to improve detection and classification accuracy and reduce memory usage. A larger dataset with more species and diverse pictures of fruits and synthetic images can be used. We would like to convert this proposed system to identify the defective and damaged fruits in the future. It would be an excellent invention for our farmers to do smart farming in this modern era.

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