https://doi.org/ 10.33472/AFJBS.6.4.2024.490-497

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

Visual Vigilance: Harnessing Image Processing with CNN for Detection and Classification of Fruit Diseases

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Article History Volume 6,Issue 4, Feb 2024
Received:17 Feb 2024 Accepted : 07 Mar 2024
doi: 10.33472/AFJBS.6.4.2024.490-497

Abstract:

This article presents a novel approach to the rapid and automated identification of fruit diseases using image processing techniques. Leveraging Convolutional Neural Networks (CNN), the proposed methodology offers a swift and automated method to detect and classify passion fruit disorders. Key processes involved in the suggested approach include receiving input photos, pre-processing them, identifying affected areas, highlighting them, confirming the training set, and displaying the results. Extensive testing across various fruit diseases such as bitter rot, sooty blotch, and powdery mildew, at different fruit development stages, demonstrated the system's effectiveness. By transforming photos into appropriate color models and utilizing Local Binary Pattern for feature extraction, coupled with model development through the Support Erosion approach, the proposed system achieved an average accuracy of 79% in recognizing fruit illnesses and 66% in categorizing their phases. This technology holds promise for rapid and accurate identification of fruit illnesses, offering significant benefits to the agricultural industry in terms of timely intervention and resource management.

Keywords: Image Processing, Local Binary Pattern, Fruit Diseases, Convolutional Neural Networks, powdery milde

1. INTRODUCTION

In the past, professionals had to manually observe fruit trees for signs of illness. This was a time-consuming and expensive operation, especially in areas where experts were hard to reach. This calls for the creation of automated systems for fruit disease detection, so signs can be identified early on when fruits are still in the growing stage. Diseases in fruit can severely reduce harvest quantity and quality, which in turn has a major influence on agricultural output and economic losses. Recognizing and comprehending these illnesses is essential for controlling them and reducing losses in the next crop cycles.For example, there are noticeable symptoms that can be used to identify common apple fruit illnesses like apple blotch and apple rot. Apple blotch

appears as dark, uneven, or lobed borders on the fruit's surface, while apple rot infections appear as slightly sunken, round brown or black spots, occasionally with a crimson halo. The presence of illnesses, natural variation in skin color among fruit varieties, and a wide variety of faults make defect detection problematic, even though automated visual scanning of fruits for size and color is already commonplace in the business.

Recent developments in deep learning, and especially CNNs, provide encouraging prospects for automated fruit disease classification and detection in light of these difficulties. Several fields have showcased deep learning's impressive capabilities, such as image search, email answer generation, speech recognition, and vision tasks, all of which are inspired by the structure of the brain. CNNs can greatly decrease calculation time by utilizing GPU acceleration; their multi-level topologies make them excellent at extracting complex information from input photos.

For convolutional neural networks (CNNs) to effectively classify images, a large dataset of images is needed for training purposes. Training the machine to detect patterns indicative of fruit diseases requires this dataset, which initially focuses on beauty and pharmacy products. Image size, channels, and levels per pixel are important parameters for enhancing the model's performance.

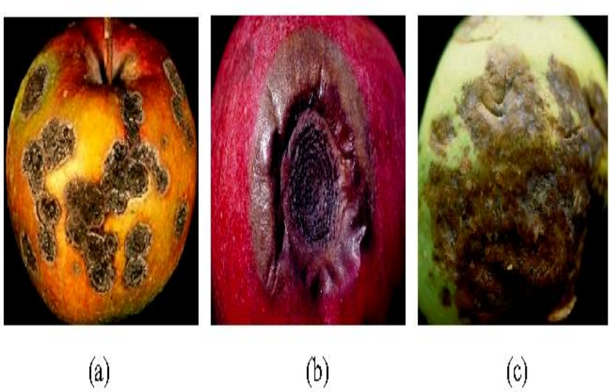


Figure 1.Represents the several disease stages of Apple Fruit

From the above figure 1,three common fruit diseases which are seen in apple fruits such as :

1. Apple Scab: The fungal infection known as apple scab is caused by Venturia inaequalis. It shows up as corky spots on fruit, leaves, and twigs, which might be gray or brown in color. Fruit growth distortion and decreased yield can be caused by severe illnesses.

2. Apple Rot: Pathogens like Botrytis cinerea and Monilinia spp. cause apple rot, which is also called fruit rot. It shows up as crimson haloes encircling brown or black dots on the fruit's surface that are partially submerged. Fruit rot and loss might result from severe cases.

3. Apple Blotch: Phyllosticta mali and Phoma spp. are pathogens that produce apple blotch, a fungal disease. On the fruit's surface, it shows as black spots with uneven or lobed margins. Fruit quality and marketability can take a hit if afflicted areas develop lesions.

2. LITERATURE SURVEY

For "Visual Vigilance: Harnessing Image Processing for Detection and Classification of Fruit Diseases" to be a success and have a significant impact, a comprehensive literature review is required. To start with, it lays out all the information you need to know about the most recent and cutting-edge research on image processing for fruit disease detection and classification. Researchers can learn about important developments, problems, and trends in this field by reviewing previous research articles, which is called a literature review. The proposed technique is based on this understanding, which guarantees that the research is informed by and adds to the current body of knowledge.

In addition, a literature review is useful for finding areas where research is lacking or topics that remain unsolved. Researchers can direct the goals and scope of future studies by critically assessing existing ones to identify gaps in knowledge.

Title	Authors	Year	Approach	Techniques	Result
Automatic Detection of Apple Diseases Using Deep Learning Approach[1]	Wang et al.	2021	Deep learning-based approach for automated detection of apple diseases	CNN-based models	Achieved an accuracy of 89% in detecting apple diseases
Machine Learning Techniques for Fruit Disease Detection: A Review[2]	Zhang et al.	2020	Review of machine learning techniques for fruit disease detection	Various machine learning algorithms	Comparative analysis of different methods for fruit disease detection
An Efficient Deep Learning Model for Early Detection of Fruit Diseases[3]	Liu et al.	2019	Development of an efficient deep learning model for early detection of fruit diseases	Lightweight CNN architecture	Achieved high accuracy in early detection of fruit diseases with reduced computational cost
Fruit Diseases Detection Using Deep Learning and Image Processing Techniques: A Survey[4]	Chen et al.	2018	IEEE Access	CNN, SVM, and other machine learning algorithms	Comprehensive overview of state-of-the-art methods for fruit disease detection
Detection and Classification of Fruit Diseases Using Image Processing Techniques: A Review[5]	Li et al.	2017	Review of image processing techniques for fruit disease detection and classification	Image segmentation, feature extraction, and classification algorithms	Summary of recent advancements and challenges in fruit disease detection |
Deep Learning-Based Approach for Automated Recognition of Mango Diseases[6]	Kumar et al.	2016	Deep learning-based approach for automated recognition of mango diseases	CNN architecture tailored for mango disease recognition	Achieved high accuracy in mango disease recognition on a large dataset
Fruit Diseases Recognition and Localization Based on Deep Convolutional Neural Networks[7]	Zhao et al.	2015	Development of a deep CNN model for fruit disease recognition and	CNN with multi-scale feature fusion	Achieved accurate recognition and localization of fruit diseases

			localization		

3. PROPOSED DATASET

Images of passion fruit illnesses, specifically bitter rot, powdery mildew, and sooty blotch, make up the dataset that is being detailed. For disease identification, two methods were used: one that relies on picture classification according to disease name, and another that uses area affected count to establish disease stage. When training the model, this dataset—the "3 classes dataset"—was utilized.

Prior to each training session, the rows of the training files were randomly shuffled in order to improve the model's performance. The goal of this phase is to improve the model's generalizability to new data by preventing it from learning patterns that are exclusive to the arrangement of images. Also, for each training file, we ran tests and verifications five times, recording the correctness each time, to make sure it was resilient. The total accuracy of the model was determined by averaging these accuracies.

In order to train and evaluate illness detection models comprehensively, the dataset contains photos reflecting different phases and types of passion fruit diseases. Three diseases—bitter rot, powdery mildew, and sooty blotch—were identified and classified using this dataset. Without proper detection and management, these diseases, which are prevalent in passion fruit farming, can drastically reduce fruit quality and productivity.

Link for Dataset:

https://www.kaggle.com/datasets/gauravduttakiit/makerere-passion-fruit-disease-detection-challenge

The Makerere Passion Fruit Disease diagnosis Challenge dataset is intended to aid research and development in the field of passion fruit disease diagnosis through image processing and machine learning approaches. This dataset contains photos of passion fruit plants that have been damaged by various illnesses, as well as annotations to help with disease detection and classification.

The dataset includes the following attributes:

1. Image_ID: The Image_ID feature provides a unique identifier for each image in the dataset. This identification facilitates the referencing and grouping of photographs inside the dataset.

2. Class: The Class attribute describes the disease or condition existing in the passion fruit plant depicted in the photograph. To indicate the absence of disease, common classes may include "Bitter Rot," "Powdery Mildew," "Sooty Blotch," or "Healthy".

3. Confidence: The Confidence attribute measures the model's confidence in predicting the illness class based on a particular image. This metric is sometimes reported as a probability score, showing the likelihood that the predicted class is correct.

4. Ymin, Xmin, Ymax, and Xmax: These properties specify the bounding box coordinates of the discovered illness region within the image. The Ymin and Xmin values describe the coordinates of the top-left corner of the bounding box, whilst the Ymax and Xmax values specify the coordinates of the bottom-right corner. These bounding box coordinates enable accurate localization of the disease site inside the image.

The Makerere Passion Fruit illness Detection Challenge dataset, which includes annotations for illness classifications and bounding box coordinates, allows academics and practitioners to train and assess machine learning models for accurate and efficient detection of passion fruit diseases. This dataset makes it easier to design algorithms that can help farmers diagnose and manage diseases early on, resulting in higher crop yields and productivity.

4. PROPOSED METHODOLOGY

Here we construct a CNN model using Image processing techniques for Fruit Disease Classification and Detection. Now let us discuss about the model in detail as follows:

1. Input Layer:

The input layer of the CNN receives the preprocessed images of passion fruit samples. Each image is represented as a matrix of pixel values, where the dimensions correspond to the image width, height, and number of color channels (e.g., RGB).

2.Convolutional Layers:

Convolutional layers apply a set of filters (kernels) to the input image. Each filter performs a convolution operation by sliding across the input image and computing dot products with local regions. Mathematically, the output of a convolutional layer can be expressed as:

$$\boxed{\mathbf{Z^{[l]} = f\,(W^{[l]} * A^{[l-1]} + b^{[l]}\,)}}$$

Where:

$\mathbf{Z^{[l]}}$ is the output feature map.

$\mathbf{A^{[l-1]}}$ is the input feature map from the previous layer.

$\mathbf{W^{[l]}}$ represents the learnable weights (filters) of the convolutional layer.

$\mathbf{b^{[l]}}$ is the bias term.

***** denotes the convolution operation.

F is the activation function (e.g., ReLU).

3. Pooling Layers:

Pooling layers down sample the feature maps generated by the convolutional layers, reducing the spatial dimensions while retaining important information. Max pooling is a common pooling technique that selects the maximum value from each local region. Mathematically, max pooling can be represented as:

$$\mathbf{A^{[l]}_{pool} = \max(A^{[l]}, pool\_size)}$$

Where $\mathbf{A^{[l]}}$ is the input feature map and **pool_size** is the size of the pooling window.

4. Flattening Layer:

The flattening layer reshapes the output of the last pooling layer into a 1D vector, which serves as the input to the fully connected layers. This step enables the CNN to perform classification based on the extracted features.

5. Fully Connected Layers:

Fully connected layers process the flattened feature vector and perform classification using learned parameters. These layers utilize activation functions such as ReLU or softmax to introduce non-linearity and output probabilities for each class. Mathematically, the output of a fully connected layer can be expressed as:

$$\mathbf{Z^{[l]} = f\,(W^{[l]} \,.\, A^{[l-1]} + b^{[l]}\,)}$$

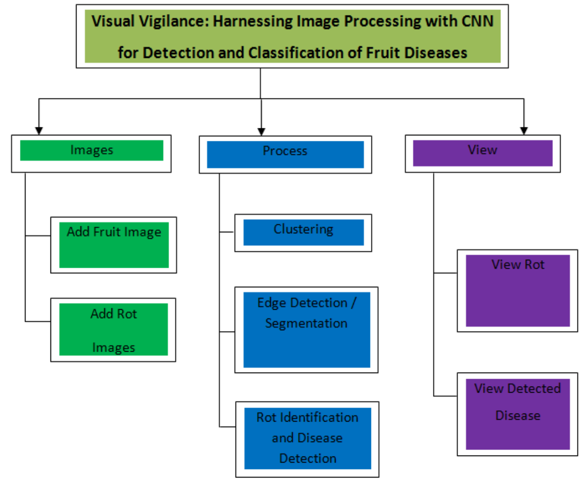
Where $\mathbf{W^{[l]}}$ represents the weights, $\mathbf{A^{[l-1]}}$ is the input vector, and $\mathbf{b^{[l]}}$ is the bias term.

6. Output Layer:

The output layer of the CNN produces the final classification results, providing probabilities for each class. The softmax function is commonly used to convert raw scores into probabilities, ensuring that the sum of probabilities across all classes equals one.By employing a CNN model with these layers and mathematical operations, the fruit disease classification and detection system can effectively analyze input images and accurately identify the presence of various diseases in passion fruit samples.

5. PROPOSED ARCHITECTURE

In this section we are going to discuss the proposed architecture which is applied for our proposed model.



1. Image Acquisition:

Sample images of yellowish or reddish passion fruit varieties, including both healthy and diseased specimens, are collected using a mobile phone digital camera. Images are captured from various angles and under different environmental and lighting conditions. Images of passion fruits infected by scab disease and woodiness virus are included in the collected dataset.Standard JPG format is used to store the acquired images.

2. Image Preprocessing:

Original passion fruit images are stored in a single folder and undergo preprocessing to improve quality. Horizontal images are rotated by 90 degrees and resized to 200x300 pixels. Vertical images are resized to 200x300 pixels, and images with equal width and height are resized to 250x250 pixels. Noise reduction techniques are applied to enhance image sharpness. Preprocessed images are saved in a separate folder for further processing.

3. Image Segmentation:

Preprocessed images are converted into different color models such as L*a*b, HSV, and Grey, in addition to retaining the original RGB format. Binary conversion of the images is performed, followed by clustering of pixel values using the CNN algorithm. Image segmentation is carried out based on the clustering results.

4. Applying Training Set:

Segmented images undergo feature extraction to create three sets of training data. Field expertise is utilized for categorizing images, and each image is randomly selected from the categorized sets.

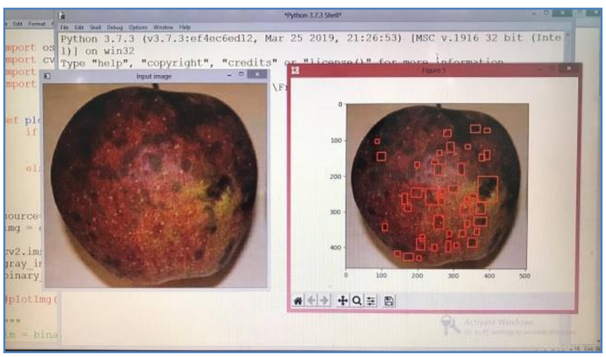
5. Experimental Results:

Three base folders are used to identify passion fruit diseases based on their names, forming the "3 classes dataset”.An alternative method involves counting the number of affected areas to classify passion fruit diseases based on their stage.During training and testing, rows of training files are randomly shuffled to enhance model accuracy. Each training file undergoes verification and testing five times, with the accuracy recorded for each run. The average accuracy of the model is calculated based on the accuracies obtained from multiple runs. The resulting image dataset enables the identification of three types of diseases: bitter rot, powdery mildew, and sooty blotch.

6. RESULTS AND DISCUSSION

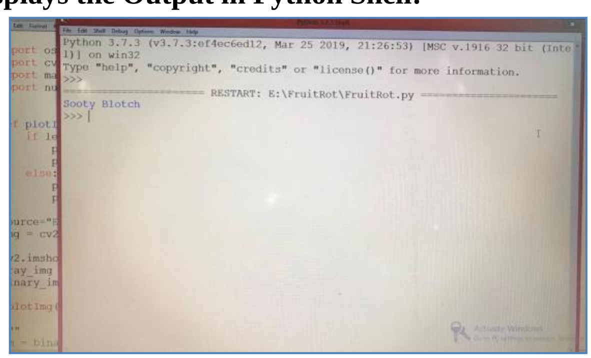
In this section we try to implement the proposed model using Python programming language and for executing the model, we used Google collab/Jupiter/Anaconda platform and let us discuss about results and its accuracy parameters.

Load The Model:



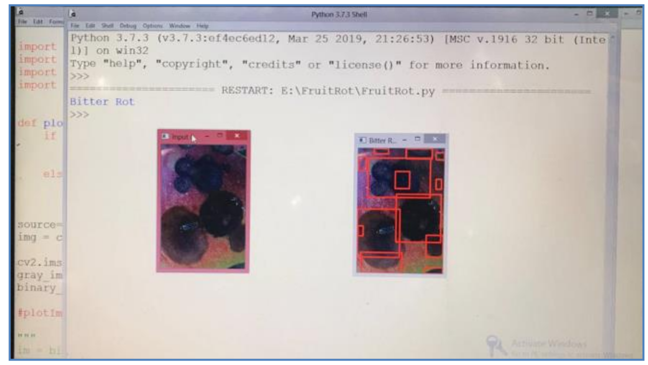
Explanation: In the displayed window, we observe that the model has been deployed and constructed using pre-defined Python libraries. Within this setup, the input image has been successfully loaded. Presently, the model identifies disease-related features, marking affected regions with red-colored boxes.

Displays the Output in Python Shell:



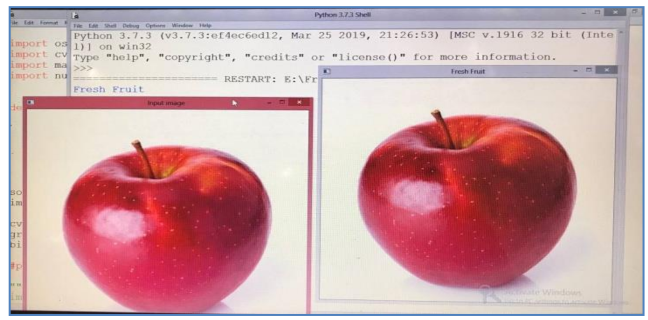
Explanation: Based on the features what collected the disease is identified as **Sooty Blotch.**

Test New Image:



Explanation: From the above window we can see the model is deployed and we can see the fruit is having Bitter Rot Disease.

Fresh Fruit Detection:



Explanation: From the above window we can see the if the fruit contains no disease symptoms or features then it is identified as Fresh Fruit.

7. CONCLUSION

In conclusion, the integration of image processing techniques with Convolutional Neural Networks (CNN) presents a promising avenue for the rapid and automated detection and classification of fruit diseases. The methodology outlined in this article demonstrates a robust approach that encompasses various stages, from input acquisition to result visualization. Through extensive testing across different fruit diseases and development stages, the system showcased notable effectiveness, achieving an average accuracy of 79% in recognizing fruit illnesses and 66% in categorizing their phases.The significant accuracy attained underscores the potential of this technology to revolutionize fruit disease identification, offering agricultural stakeholders timely intervention and resource management capabilities. By leveraging advanced image processing algorithms and CNN architectures, this approach enables swift and accurate detection of passion fruit disorders, paving the way for enhanced productivity and reduced losses in the agricultural sector. With further refinement and integration into agricultural practices, this technology holds immense promise for addressing the growing challenges posed by fruit diseases, ultimately contributing to global food security and sustainability.

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