Fruit Disease Prediction Using Deep Learning Algorithm-Survey Paper

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Abstract - Agriculture serves multiple purposes, such as providing food, energy and addressing global warming. However, plant diseases can significantly impact crop quality and quantity, making their early diagnosis crucial. Currently, plant diseases are identified through the naked eye method, which requires experts to detect changes in leaf color. This approach is time-consuming, impractical for large fields, and can be expensive. Additionally, different experts may identify the same disease as different ones. Failure to detect and treat plant diseases early can result in economic disaster for producers, particularly those in remote regions. To address this issue, machine learning algorithms can be utilized for plant monitoring through image segmentation and classification using methods such as Otsu thresholding and convolutional neural networks. This approach can offer a more affordable alternative to hiring professional agriculturists while still providing accurate disease detection.

Index Terms - Disease prediction, Features Extraction, Segmentation, Classification, Neural network

I.INTRODUCTION

India is a country that relies heavily on agriculture, and farmers have a wide range of fruit and vegetable crops to choose from. Recent research has developed an advanced computing system that utilizes infected images of various leaf spots to identify diseases. The images are captured using digital cameras and processed through image growing, with a portion of the leaf spot used for classification during training and testing. This system combines image processing and advanced computing techniques. Agricultural research aims to increase the quality and quantity of products while minimizing expenses and maximizing profits. Plant diseases caused by pathogens like fungi, bacteria, and viruses can significantly degrade the quality of agricultural products. Early detection and classification of these diseases is crucial, but constant monitoring by experts can be costly and time-consuming for farmers. To address this issue, various systems have been proposed that use image processing and automatic classification tools to reduce these problems.

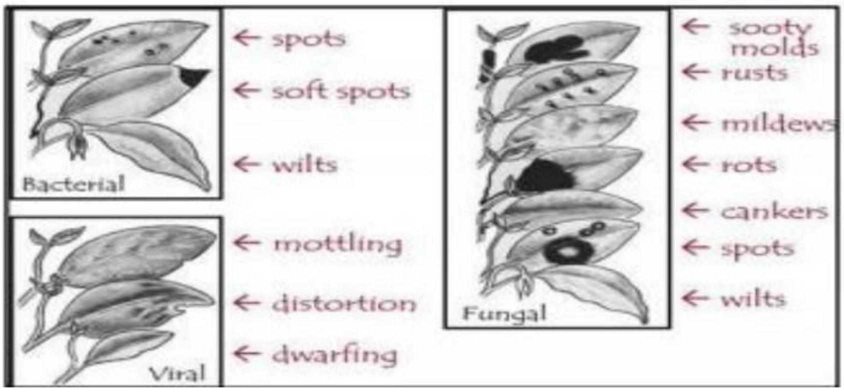

Fig 1. Various types of diseases

Most leaf diseases are caused by fungi, bacteria, and viruses, and their identification relies on their physical characteristics, such as reproductive structures for fungi. Fig. 1 shows various types of diseases which occur in plants. Bacteria, in contrast to fungi, have simpler life cycles and mostly exist as single cells that divide through binary fission. Viruses, on the other hand, are extremely small particles consisting of genetic material and protein. In biological research, a large number of images can be generated in a single experiment, which may require further analysis such as lesion classification, quantitative trait scoring, or area calculation. However, manual processing or the use of distinct software packages can be time-consuming and subjective due to individual variability. To conduct high-throughput experiments, plant biologists need efficient computer software for automatic content extraction and analysis. Image processing techniques can play a crucial role in this regard, and this project aims to provide such techniques for studying leaf diseases. Fruit diseases pose a serious threat to agricultural production, impacting both the quality and quantity of the products. Currently, experts rely on naked-eye observation to detect and identify normal and infected apples, which can be a costly and time-consuming approach. However, computer vision techniques based on machine learning can aid in early detection and treatment of diseases. Extracting features such as color, shape, and texture can aid in identifying apple structures and characteristics, and pattern recognition systems can combine multiple features to classify and identify normal and infected fruit. This method can be used in various fields, such as education, food packaging, and plant science research, as a useful image-processing tool for object classification and recognition. The fruit diseases are shown in Fig 2.

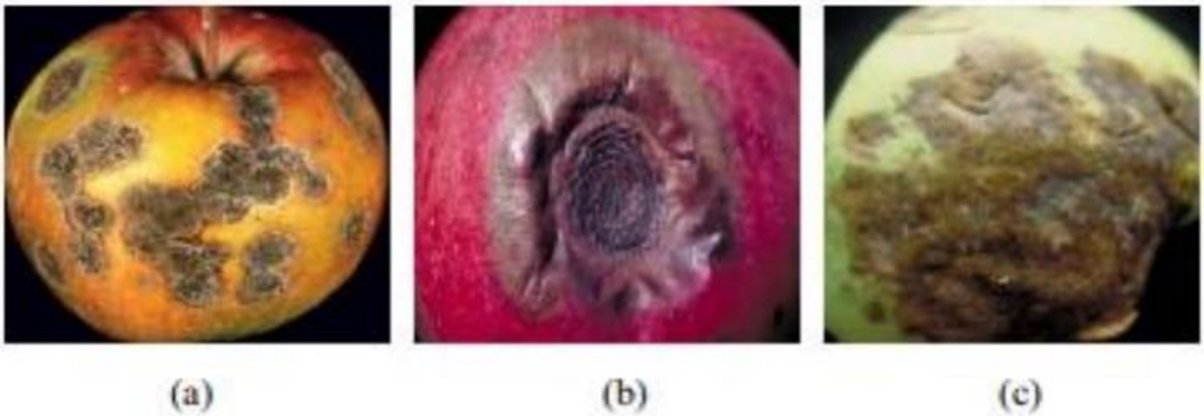

Fig 2. Fruit diseases a) apple scab b) apple rot c) apple blotch

II.RELATED WORK

The identification of plant species from field observation requires specialized botanical knowledge, which is a challenge for many people, including conservationists, farmers, and landscape architects. The shortage of skilled taxonomists further exacerbates this problem. To overcome this challenge, taxonomists are exploring new methods such as digital image processing and pattern recognition techniques. These technologies are made possible due to the development and ubiquity of relevant information technologies such as digital cameras and portable devices. Deep learning, a class of machine learning techniques that enable representation learning of multiple level data abstraction, is used for automatic processing and classification of plant species. This approach allows the discovery of useful features for leaf data and provides a better solution to the classification task, as it considers the variability in natural object kinds, including plant species. The present study uses deep learning to interpret and elicit the particular features that best represent leaf data, instead of creating feature representation as in previous approaches. The results show a layer-by-layer transition from general to specific types of leaf features, similar to the botanists' character definitions used for plant species classification.
Knowing the identity, location, and uses of plants is important for sustainable agriculture and biodiversity conservation. However, this information is often incomplete, making it difficult for professionals and the public to identify plant species. To address this issue, a collaborative workflow was developed that focuses on image-based plant identification. A citizen science project was initiated in 2010, which collected hundreds of thousands of geo-tagged plant photos and revised them by novice, amateur, and expert botanists through a social network. An image-based identification tool was created, which works with up to five different plant organs, allowing users to query the system at any time of the year. The tool is available as a web and mobile application, and users can enrich the system with new observations. Experiments and evaluations show that the tool is helpful in identifying a plant among hundreds or thousands of species. The tool is expected to speed up the collection and integration of raw botanical data, leading to a more sustainable agriculture and biodiversity conservation.
A study by A. R. Sfar and colleagues focused on fine-grained categorization, which involves recognizing sub-categories of a basic category, such as botanical species from leaf images. While people can easily recognize basic categories, identifying fine-grained categories requires expertise due to the subtle differences between sub-categories. The study investigated the use of human involvement in semi-automated systems to improve the accuracy of identification, without sacrificing efficiency. The standard scenario involves an automated system providing a single estimate of the species, but this approach may be insufficient due to high error rates in large databases with similar species and high variability. The proposed system utilises domain-specific knowledge about landmarks and taxonomy to build a hierarchical representation of species based on leaf characteristics, and offers different identification scenarios to deal with cluttered leaf images without segmentation algorithms. The results of the study showed improvement in identification accuracy compared to previous work.
J. Chaki, et. al, [5] developed a system for recognizing plant species based on their leaf images, which is important for conservation efforts as many plant species are threatened due to deforestation. The system utilises computer vision and pattern recognition techniques to represent leaf characteristics such as shape and texture using computer recognizable features. These features are fed into two neural-based classifiers to discriminate them into predefined classes. The proposed approach combines texture and shape modelling techniques, which are significant parameters for discrimination. Texture is captured using complex Gabor filter and gray level co-occurrence matrix while shape is captured using curvelet transforms and invariant moments. However, the generated feature values are sensitive to the size and orientation of the leaf image. The system aims to build a plant database for quick and efficient classification and recognition, which is essential for their conservation and preservation.

III. PROPOSED METHODOLOGY

The Folia application aims to create a system for analyzing the shape of tree leaves in natural environments to identify different species. This application is intended as an educational tool and relies on high-level geometric criteria inspired by those used by botanists to classify leaves into a list of species. Digital image processing is used to improve image quality and obtain more information from the image. Image segmentation is a mid-level processing technique used to analyze the image and classify or cluster an image into several disjoint parts by grouping pixels to form a region of homogeneity based on the pixel characteristics. However, the criteria for segmenting the image vary from image to image and can be challenging to decide. In some cases, interactive methods may be time-consuming or error-prone, and a fully automated approach can give error output. The shape, margin, and texture of leaves and fruits are essential features to identify different species. A study on the segmentation of leaf images is restricted to semi-controlled conditions, in which leaves or fruits are photographed against a solid light-colored background. Several popular segmentation algorithms are evaluated on this task. The identification of species is the first key to understanding the plant environment. The use of leaves or fruits, which are easy to photograph and analyze from two-dimensional images, is the most sensible approach in image processing for non-specialist-oriented applications. In the process of tree identification from pictures of leaves in a natural background, retrieving an accurate contour is a challenging and crucial issue. In this project, a method is introduced to deal with complex images for simple and lobed tree leaves and fruits. A first segmentation step based on a light polygonal leaf or fruit model is performed, and later used to guide the evolution of an Otsu threshold. The leaves and fruits are then classified using global shape descriptors given by the threshold model with local curvature-based features. Finally, a convolutional neural network classification algorithm is implemented to classify fruit and leaf diseases. The proposed framework is shown in Fig 3.

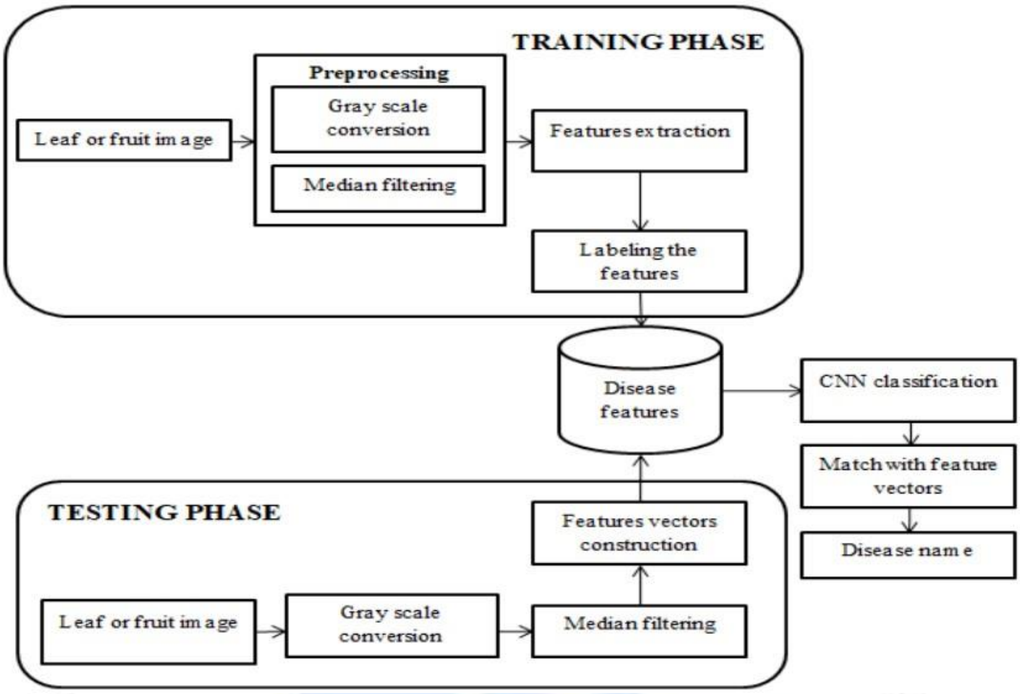

Fig 3. Proposed work

In image acquisition stage, it is possible to upload images of leaves or fruits from various datasets. The images can be of any size or format, and the module is specifically designed to work with images of apples, grapes, pomegranates, and their respective leaves. Preprocessing is the first step in identifying plants based on their leaves and fruits is to convert the RGB image into grayscale. The reason for this is that the color feature is not always reliable due to changes in the atmosphere. Therefore, before pre-processing the image, it is necessary to convert it from RGB to grayscale. The conversion formula from RGB to grayscale is provided in an equation, and it ensures that the grayscale image retains the necessary information for plant recognition. This median filtering process is shown in Fig. 4. Thresholds are shown in equation (1).

Gray = 0.2989 * R + 0.5870 * G + 0.1140 * B………[1]

where R, G, B correspond to the colour of the pixel, respectively

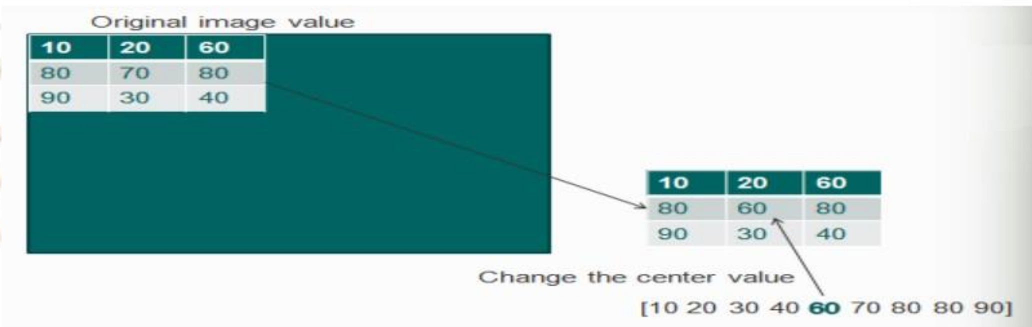

Fig 4. Median filtering

Next, the images are processed to remove any unwanted noise using filtering techniques. The purpose of the filter is to eliminate any disturbances that may have distorted the image. The filter's design is based on a statistical approach and is used to achieve a specific frequency response. In image processing, filtering is a nonlinear operation that is commonly used to decrease the impact of "salt and pepper" noise. When the goal is to both reduce noise and maintain edges, a median filter is more effective than convolution. Finally, image binarization tasks are carried out. This module proposes a technique for image segmentation using Otsu's thresholding and automatic descriptors. The segmentation of foreground objects in images with stationary background can be achieved through background subtraction techniques. However, complex factors such as specular reflections, background clutter, shading, and shadows can impact the system's effectiveness. Therefore, it is beneficial to perform image segmentation focused solely on the object's description. Otsu's method is used in the first step of this technique to segment the image by taking the threshold value based on extensive image analysis. The algorithm assumes that there are two classes of pixels in the image, foreground and background, and calculates the optimal threshold to separate them by minimizing their combined spread or maximizing their inter-class variance. The health of leaves and fruits can be negatively impacted by various factors such as bacteria, fungi, viruses, and insects. To evaluate the quality of fruits and leaves, convolutional neural networks (CNN) are widely used. Artificial neural network (ANN) algorithms can also be used to classify images of leaves and fruits as either healthy or diseased. The ANN is designed to minimize errors and achieve good results on testing data sets by constructing vectors based on features such as color, shape, and texture of the leaves. CNNs are modelled after biological neural networks and consist of connected units called artificial neurons. The connections between neurons, called edges, transmit signals, and the neurons process these signals and signal other connected neurons. In typical CNN implementations, the signal is a real number, and the output of each neuron is computed by a nonlinear function. The weights and biases of the neurons are adjusted during learning to improve accuracy. Training and learning functions are used to adjust the weights and biases. Ultimately, the system can classify leaves and fruits with disease names and achieve high accuracy rates.

IV. CONCLUSION

The paper provides an overview of several techniques and algorithms that have been proposed for segmentation and classification methods to improve the quality of segmentation. The authors present a method for segmenting a leaf in a natural scene, which involves optimizing a polygonal leaf model and applying an exact otsu threshold segmentation. The segmentation process utilizes a color model that is robust to uncontrolled lighting conditions, but the authors suggest that an additional texture model or adaptive color model could further improve the segmentation. The method also involves extracting global geometric descriptors and local curvature-based features on the final contour, which are then used for classification into tree species. Additionally, the authors propose implementing a convolutional neural network classification algorithm to identify diseases in leaves and fruits such as apples, grapes, and pomegranates. They suggest that the framework can be extended to implement various deep-learning classification algorithms for various vegetables, resulting in improved accuracy rates.

V. REFERENCES

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