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Plant Leaf Disease Detection Robot

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Abstract— The key motivation for developing the convolutional networks model for leaf disease is to provide the farmers with an easy-to-use system to detect early-stage infections by using common digital camera. Second, extracting effective features for identifying diseases is a critical but challenging task, and CNNs are highly expected to be automated feature learning from the raw inputs in a systematic way.

***Index Terms*—Image processing, CNN, smart agriculture, crop yield improvement, leaf disease detection.**

1. Introduction

Sorghum is one of the main coarse cereal crops of India. India is the second-largest producer of sorghum in the world. This crop is ideally suited for semi-arid agroclimatic regions of the country and gives reasonably good yield with minimal requirement of irrigation and fertilizers as compared to other cereals such as Wheat & rice. Sorghum is grown in the kharif (rainy season) and rabbi (post rainy season) but the share of kharif is higher both in terms of area under cultivation and production. However, in recent years, the number of species of sorghum diseases and the degree of harm they cause have increased, mainly due to changes in cultivation systems, the variation of pathogen varieties, and inadequate plant protection measures.

The goal of this research is to construct a deep convolutional networks model to achieve fast and accurate automated detection by using sorghum leaf disease images. Generally, there are five types of common leaf diseases, including Sorghum leaf blight, Sooty stripe, Leaf rust and gray leaf spot, Bacterial leaf spot and zonate leaf spot. Sorghum leaf diseases have various symptoms. It may be more difficult for inexperienced farmers to detect diseases than for professional plant pathologists. As a verification system in disease detection, an automatic system that is designed to identify crop diseases by the crop's appearance and visual symptoms could be of great help to farmers.

Many efforts have been applied to the quick and accurate detection of leaf diseases. By using digital image processing techniques and neural networks, we can detect and classify leaf diseases. Deep learning has made tremendous advances in the past few years. It is now able to extract useful feature representations from a large number of input images. Deep learning provides an opportunity for detectors to identify crop diseases in a timely and accurate manner, which will not only improve the accuracy of plant protection but also expand the scope of computer vision in the field of precision agriculture.

2. Methodology

Here we first take leaf image as an input and further preprocessing on that image is carried out. Preprocessing of image consists of some basic steps such as: RGB to gray conversion, edge detection etc. After that feature extraction of the same image is carried out. In this system we have data set of images of which 80% of images are used for training and 20% are used for testing purpose. Then depending upon the machine learning algorithm classification and detection of normal and abnormal images is done and the abnormal images are identified as per the predefined diseases.

Elements of Block Diagram: Below mentioned are the elements of block diagram of the proposed system. 1. Pre-processing block 2. Alex-net algorithm 3. Classification and detection

Pre-processing of Image: Pre-processing refers to the transformations applied to our data before feeding it to the algorithm. Data Pre-processing is a technique that is used to convert the raw data into a clean data set. Some of the point processing techniques include: contrast stretching, global thresholding, histogram equalization, log transformations and power law transformations. Some mask processing techniques include averaging filters, sharpening filters,local thresholding, etc.

Alex-Net Algorithm: Alex-Net is a Deep Convolutional Neural Network for image classification. AlexNet has 8 layers. The first 5 are Convolutional and the last 3 are fully connected layers. In between there are some layers called pooling and activation. It has Multiple Convolutional Kernels (a.k.a filters) extract interesting features in an image.

Detection and Classification of Image: In Machine Learning Decision Tree is one of the predictive modelling approaches used in statistics. Decision trees are constructed via an algorithmic approach that identifies ways to split a data set based on different conditions. Decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes.

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3. Features

1. *Early-stage disease detection*: The system aims to detect plant diseases at an early stage using a common digital camera.
2. *Automated system*: The project focuses on creating an automated system for regular monitoring of cultivated areas and automated disease detection.
3. *Convolutional Neural Networks (CNNs)*: The system utilizes CNNs to analyze leaf images and identify diseases.
4. *Image processing techniques*: Digital image processing techniques are employed for tasks such as RGB to grayscale conversion, edge detection, thresholding, and noise reduction.
5. *Classification and detection*: The system classifies leaf images as either normal or abnormal and identifies specific diseases
6. *Hardware components*: The hardware setup includes a camera, Raspberry Pi, float sensor, and possibly a sprinkler system.
7. *Software implementation*: The software is developed using Python and Anaconda, with libraries like Spyder and PyCharm.

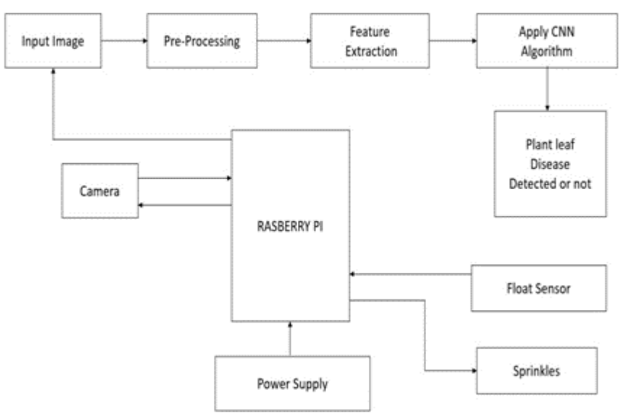

Fig. 1. System architecture

4. Algorithms Used

1. *Image Acquisition and Preprocessing*: Images of plant leaves are captured by the robot's camera. These images can be of different resolutions and lighting conditions, so preprocessing is important. Preprocessing steps can include resizing images to a uniform size, normalizing pixel values, and sometimes applying data augmentation (such as rotation, zoom, or flip) to make the model more robust.
2. *Convolutional Layers*: CNNs consist of convolutional layers where filters (also called kernels) are applied to the image. These filters move across the image and extract important features, such as edges, shapes, and textures, which can signify the presence of disease patterns. In leaf disease detection, the initial layers of the CNN might detect basic patterns like edges of spots or lesions, while deeper layers capture more complex shapes and features specific to different diseases.
3. *Pooling Layers*: After each convolutional layer, pooling layers (typically max pooling) reduce the spatial dimensions of the feature maps. This reduces the number of parameters, speeds up computation, and helps the CNN become more invariant to small transformations (like shifts or slight rotations) in the image. Pooling helps the model focus on the most prominent features in the leaf images, which is useful for identifying specific disease characteristics.
4. *Fully Connected Layers*: Toward the end of the CNN, fully connected (FC) layers connect all neurons from the previous layer. These layers act as a classifier, interpreting the high-level features learned by the convolutional layers to make final predictions. For disease detection, the output layer will typically have as many nodes as the number of classes (i.e., types of diseases plus one for healthy leaves), and it may use softmax activation to output probabilities for each class.
5. *Training and Optimization*: The CNN is trained using a labeled dataset of healthy and diseased leaf images. During training, the CNN adjusts its filter weights to minimize prediction errors using a loss function (often categorical cross-entropy for multi-class classification). Optimizers, like Adam or SGD, are used to update the weights through backpropagation. After training, the CNN learns to accurately classify images based on patterns and features that correspond to specific leaf diseases.
6. *Deployment on IoT-Based Smart Agriculture*: Robot Once trained, the CNN model is deployed on the IoT-enabled robot. When the robot encounters a new leaf, it captures an image, preprocesses it, and passes it through the CNN for real-time disease classification. The IoT system can then alert the farmer about detected diseases and may trigger other responses.

5. Testing

Testing is an investigation conducted to provide stakeholders with information about the quality of the product or service under test. Software testing also provides an objective, independent view of the software to allow the business to appreciate and understand the risks of software implementation. Test techniques include, but are not limited to, the process of executing a program or application with the intent of finding software bugs. Software testing can also be stated as the process of validating and verifying that a software program or application or product:

1. Meets the business and technical requirements that guided its design and development.
2. Works as expected and can be implemented with the same characteristics

Software testing, depending on the testing method employed, can be implemented at any time in the development process. However, most of the test effort occurs after the requirements have been defined and the coding process has been completed. As such, the methodology of the test is governed by the software development methodology adopted. Different software development models will focus the test effort at different points in the development process. Newer development models, such as Agile, often employ test driven development and place an increased portion of the testing in the hands of the developer, before it reaches a formal team of testers. In a more traditional model, most of the test execution occurs after the requirements have been defined and the coding process has been completed.

A. Results and Discussion

A grayscale image is one in which the value of each pixel is a single sample representing only an amount of light, that is, it carries only intensity information. Grayscale images, a kind of black-and-white or gray monochrome, are composed exclusively of shades of gray. The contrast ranges from black at the weakest intensity to white at the strongest.

Image segmentation is the most important task in many image processing systems, such as pattern recognition, image retrieval and small surveillance. The result of segmentation is mainly used for image content understanding and visual object recognition through the identification of region of interest. Image segmentation is used to locate objects and boundaries (lines, curves, etc.) in images and assigns a label to every pixel in an image, in a manner that pixels with the same label share certain visual characteristics. Also, the result of image segmentation is a set of regions that collectively cover the entire image, where each pixel in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture.

B. Conclusion

Sorghum crop diseases can earn tremendous amount of loss in agriculture if sufficient attention is not given. Using computer and communication technologies, an automated system can be built which can provide early notification of disease. ALEX-NETs is a valuable pattern-recognition method both in theory and in application. In this paper, we proposed an innovative technique to enhance the deep learning ability of ALEXNETs. The proposed ALEX-NETs based model can effectively classify common diseases through images recognition. The application to the Sorghum leaf disease detection shows that the proposed ALEX-NETs model can correctly and effectively recognize Sorghum leaf diseases through image recognition. ALEX-NETs are very good feature extractors. This means that we can extract useful attributes from an already trained ALEX-NET with its trained weights by feeding your data on each level and tune the ALEX-NET a bit for the specific task. In this study we have implemented techniques of the image processing and machine learning that have been used sorghum leaf disease detection and classification.

C. Future Scope

The machine learning approach led to a powerful leaf identification system that performs better than state-of the- art systems. Extend our system by using machine learning and correctly process the extracted features.

1. Designing a completely automated system where remote sensing techniques for acquisition of spectral image by satellite imagery, airborne images from chartered or model planes are used.
2. A prediction approach based on convolution neural network for developing weather-based prediction models of plant diseases

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