



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Special Issue 2, April 2023

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

9940 572 462

6381 907 438

ijrset@gmail.com

www.ijrset.com

Image Processing and Deep Learning Algorithms: An Application for Plant Leaf Disease Detection and Classification

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ABSTRACT: In order to detect plant leaf disease for an automated vision system utilised in an agricultural field, the project employs deep learning and image processing techniques. Plant diseases are a significant factor since they significantly reduce the quality and yield of agricultural products. We provide a solution based on deep learning that automates the process of disease classification for the leaves. We employ convolutional neural networks in order to classify digital image dataset. The preliminary results show that the suggested approach is effective even in difficult situations like light, complicated backgrounds, and images of genuine scenes with varying resolutions, sizes, poses, and orientations.

KEYWORDS: Deep learning, Plant leaf disease detection, Classification, Image processing.

I. INTRODUCTION

Almost 70% of the population of India depends on agriculture. Farmers can select the best insecticides for their plants from a wide range of appropriate crops. Crop damage would therefore lead to a large loss in productivity, which would have an effect on the economy. The most fragile component of plants, the leaves, are where disease symptoms first appear. From the very beginning of their life cycle until the point at which they are ready for harvest, the crops must be kept under close observation for disease. Initially, specialists manually observed crop fields using the time-consuming method of traditional naked eye surveillance to keep a check on the plants for diseases. The development of automatic and semiautomatic plant disease detection systems has used a variety of methodologies recently, and automatic disease detection by simply observing symptoms on plant leaves is now easier and less expensive. As of now, these methods have proven to be quicker, less expensive, and more precise than the conventional approach of manual observation by farmers. The majority of the time, disease symptoms are visible in the fruit, stem, and leaves. Considered for disease detection is a plant leaf that exhibits disease signs. Farmers generally don't have a thorough understanding of the crops and diseases that can impact them. Farmers can successfully employ this specified effort to increase yield as compared to contacting an expert and seeking their guidance. The major goal is to implement image processing technology to not only identify the disease, but also to guide the user to an e-commerce website where they can compare prices, buy the necessary pesticides, and use them correctly in accordance with the instructions.

II. RELATED WORK

The five common apple diseases Alternaria leaf spot, Brown spot, Mosaic, Grey spot, and Rust all significantly reduce apple yield. To ensure the healthy development of the apple business, the current research does not yet have an accurate and quick detector of apple disease. It is possible to think of object detection algorithms like SSD, DSSD, and R-SSD as having two parts: The pre-network model, which serves as an essential features extractor, is the initial section. One uses a multi-scale feature map for a detection, and the other uses an auxiliary structure.

The leaf image is divided into four clusters using a K-means segmentation and the squared Euclidean distances. For both colour and texture features, the Colour Cooccurrence technique is used for feature extraction. Finally, the back propagation-based neural network detection approach is used to complete classification. The total system's accuracy in identifying and classifying diseases was determined to be 93%.

To find fungal diseases on plant leaves, a variety of crop types including fruit crops, vegetable crops, cereal crops, and commercial crops are used. Each variety of crop has been treated with a different approach. The segmentation approach utilised for fruit crops is k-means clustering, while texture features have been concentrated on and identified using ANN and closest neighbour algorithms, resulting in an overall average accuracy of 90.723%. For vegetable crops, the Chan-Vase method was utilised for segmentation, local binary patterns were employed to extract texture features, and SVM and the k closest neighbour approach were used to classify the crops with an overall average accuracy of 87.825%.

Grab-cut algorithm was used to segment the commercial crops. Mahalanobis distance and PNN have been used as classifiers in wavelet-based feature extraction, with an overall average accuracy of 84.825%. Using canny edge detector and k means clustering, the cereal crops have been divided into segments. Features have been retrieved for colour, shape, texture, colour texture, and random transform. The combined average accuracy using SVM and closest neighbour classifiers was 83.72%. The health of the chilli plant can be assessed using a photograph of a leaf from a chilli plant. Their strategy is to limit the application of the Chemicals to the infected chilli plant. For feature extraction and picture recognition, they employed MATLAB. Pre-processing is carried out in this suggested study employing edge detection, Fourier filtering, and morphological procedures. The paradigm of image processing for object classification is expanded by computer vision. Here, the GUI is built using the LABVIEW software tool and a digital camera for picture capture.

For the purpose of tracking and managing plant diseases, a system based on FPGA and DSP technology has been developed. For monitoring and troubleshooting, the field plant picture or video data is obtained using the FPGA. The video or picture data is processed and encoded using the DSP TMS320DM642. Data transport uses the nRF24L01 single chip 2.4 GHz radio transmitter. It uses multi-channel wireless connection to reduce the cost of the entire system and features two data compression and transmission methods to accommodate diverse user needs.

Convolutional neural networks were used by Garima Shrestha et al. to identify the plant disease. With 88.80% accuracy, authors were able to effectively classify 12 plant diseases. The experimentation used a collection of 3000 high resolution RGB photos. Three blocks of convolutional and pooling layers make up the network. This increases the network's computing cost. Also, the model's F1 score is 0.12, which is extremely poor due to the huge amount of false negative predictions.

The Bacterial Blight Detection System for Pomegranate Plant was created by Sharath D. M. et al. employing features like colour, mean, homogeneity, SD, variance, correlation, entropy, edges, etc. For the purpose of segmenting the image's region of interest, authors used grab cut segmentation. The edges of the photos were extracted using Canny edge detector. A technique that can accurately forecast the level of fruit infection has been created by the authors.

Hyperspectral imaging has been used to detect plant diseases, as shown by Peyman Moghadam et al. This study made use of the visible, near-infrared (VNIR), and short-wave infrared (SWIR) spectrums. For the segmentation of leaves, authors used the k-means clustering approach in the spectral domain. For the purpose of removing the grid from hyperspectral images, they have presented a novel grid removal algorithm. The accuracy of the authors' vegetation indices in the VNIR spectral band was 83%, while their overall spectrum accuracy was 93%. Despite the fact that the suggested method produced improved accuracy, it is too expensive because it calls for a hyperspectral camera with 324 spectral bands.

In their research, Shiroop Madiwalar and Medha Wyawahare examined various image processing techniques for detecting plant diseases. The ability to detect plant illness using colour and texture traits was examined by authors. Using the dataset of 110 RGB photos, they tested their algorithms. The GLCM features, the mean and standard deviation of the image convolved with the Gabor filter, and the mean and standard deviation of the RGB and YCbCr channels were the features retrieved for classification. For classification, a support vector machine classifier was employed. The authors came to the conclusion that GCLM traits are useful for spotting healthy leaves. Whereas colour features and Gabor filter features are thought to be the best for spotting leaf spots and anthracnose-affected leaves, respectively. Using all the collected features, they were able to reach the greatest accuracy of 83.34%.

S. Khirade et al. used back propagation neural networks and digital image processing to solve the problem of plant disease identification (BPNN). Writers have developed many methods for spotting plant diseases using

photographs of the leaves. To segment the contaminated portion of the leaf, they used Otsu's thresholding, border detection, and spot detection algorithms. Then, for the purpose of classifying plant diseases, they extracted properties such as colour, texture, morphology, edges, etc. For classification, or to find the plant disease, BPNN is utilised.

To separate the unhealthy area of the leaf, Pushpa et al. employed the Indices Based Histogram approach. Slice segmentation, polygon approximation, and mean-shift segmentation have all been overcome by the authors. According to Kaleem et al., pre-processing involved resizing the photos to 300 300 pixels in size, eliminating background noise, boosting brightness, and adjusting the contrast. SVM classifier is utilised to categorise leaf diseases, while K-means clustering is employed for segmentation and the extraction of important information.

To enhance the quality, Sa'ed Abed applied scaling and stretching (min-max linear) to the input samples. The HIS model has been created and will be segmented later. For the purpose of segmenting the samples, mixed Euclidean distance and K-mean clustering approaches are used. For feature extraction and classification, the GLCM and SVM are employed, respectively.

The samples of plant leaves used by Vijai Singh et al. were taken with a digital camera and included samples of rose/beans (bacterial disease), lemon (sun burn disorder), banana (early scorch), and beans (fungal). With the thresholding process, the green areas serve as the background. Ultimately, the segmented image is obtained using the genetic algorithm. The colour co-occurrence is modified to enable useful feature extraction from segmented images. For classification purposes, the Minimal Distance Criterion is utilised first, followed by the SVM classifier. The recorded average accuracy is 97.6%.

An algorithm was categorised by authors in the publication "A study of algorithms for medical picture segmentation and their applications to the female pelvic cavity" based on the main approaches. Each category's algorithms are covered along with key concepts, potential applications, benefits, and An algorithm was categorised by authors in the publication "A study of algorithms for medical picture segmentation and their applications to the female pelvic cavity" based on the main approaches. Each category's algorithms are reviewed, and the key concepts, application areas, benefits, and drawbacks are distilled. Studies that segment the female pelvic cavity's tissues and organs using these algorithms are intended to highlight the distinctive qualities of each segment. In the last, the important guidelines for building the segmentation algorithms of the pelvic cavity are presented.

According to Tavares, tasks including segmentation, extraction of representative features, matching, alignment, tracking, motion analysis, deformation estimation, and 3D reconstruction make computational image analysis difficult. They employed techniques for evaluating and processing objects in photographs, and they suggested using these techniques in the fields of engineering, materials science, medicine, and biomechanics.

III.METHODOLOGY

The four phases of the plant disease detection system's process are depicted in Figure 3.1. Images are acquired during the first phase using a digital camera, a mobile device, or the internet. The image is divided into varying numbers of clusters in the second phase, each of which can be treated using a different technique. The methods for feature extraction are covered in the following phase, and illness classification is covered in the final step.

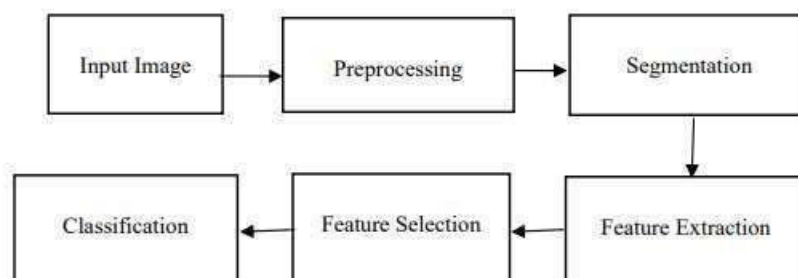


Fig 3.1 phases of a system for detecting plant diseases

Image Acquisition:

Images of plant leaves are gathered at this period using digital devices like cameras, smartphones, etc. with the chosen size and resolution. Moreover, photos from the web can be used. The application system developer is solely responsible for creating the picture database. The final phase of the detection system's classifier is more effective thanks to the image database.

Image Segmentation:

Being the foundation for feature extraction, image segmentation is also the basic method of image processing. Its goal is to simplify the representation of an image so that it is more understandable and simpler to analyse.

Feature Extraction:

Hence, in this step the features from this area of interest need to be extracted. In order to interpret a sample image, several features are required. Colour, form, and texture are all valid bases for defining features. The majority of scientists are now looking at using textural traits to identify plant illnesses. Statistically speaking, the GLCM approach classifies textures.

Classification:

Fully connected layers are used for classification, and convolutional and pooling layers are used for feature extraction. The classification procedure determines whether a plant leaf is diseased or not, what kind of disease it is, and what kind of plant it is.

Algorithm:

Convolutional Neural Network (CNN):

Artificial neural networks are used in the field of deep learning, a branch of artificial intelligence and machine learning (ANN). Deep learning model training splits feature extraction into its component parts and extracts its features for classification.

A CNN with nominal procedure may simply detect and categorise. Due to its multi-layered structure, it is effective at analysing graphical images and extracting their key characteristics. The four layers of the CNN are input image, convolutional layer and pooling layer, fully connected layers, and output, as depicted in Fig. 3.2.

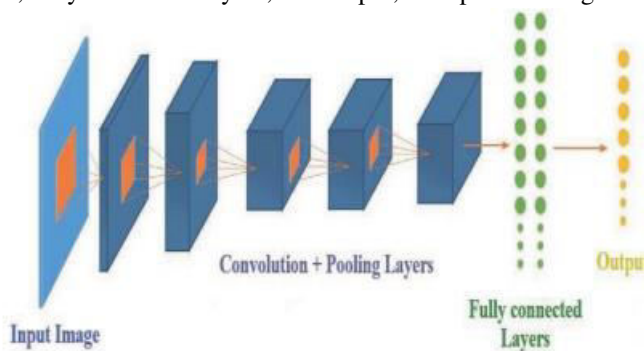


Fig 3.2 Convolutional Neural Network Architecture Illustration

A. Convolutional Layer:

The output of the kernels from the preceding layer, which comprises of learnable weights and biases, is stored in convolutional layers. The goal of the optimization function is to produce kernels that accurately represent the data. To extract the feature map of the input image, a series of mathematical operations are carried out in this layer.

B. Pooling Layer:

In addition to lowering the neuron size for the down sampling layer, this layer also prevents overfitting. This layer decreases the size of the feature map, the number of parameters, training time, computation rate, and overfitting model is said to be overfit when it achieves 100% on the training dataset and 50% on the test data. ReLU and max pooling were used to reduce the size of the feature map.

- C. Activation Layer:
each convolution layer makes use of a non-linear ReLU (Rectified Linear Unit) activation layer. Moreover, dropout layers are used in this layer to avoid overfitting.
- D. Fully Connected Layer:
The output of this layer, which is utilised to examine class probabilities, serves as the classifier's input. The well-known input classifier Softmax is used in this layer to identify and categorise illnesses of sugarcane.

IV. EXPERIMENTAL RESULTS

Disease detection and identification is done by applying image processing and machine learning methods. The "plant village dataset" dataset, which we have only chosen 25 classes out of a total of 38, was gathered from the Kaggle website. It contains various photos of both healthy and diseased crop leaves. The convolutional neural network is used to identify plant diseases with greater precision. The accuracy produced by CNN will be 90%, which is higher than the accuracy produced by hard coding methods. With early disease detection, this effort will help to automatically identify plant leaf disease and boost agricultural production.

V. CONCLUSION

The purpose of this application is to distinguish between healthy plants and plants that have diseases. The proposed research focuses on accuracy values under actual field circumstances. A number of photographs of plant diseases are taken in order to complete this work. The overall accuracy of this effort, which was started from scratch, is 93%. In order to improve accuracy, further work will involve increasing the number of photographs in the preconfigured database and changing the architecture to match the dataset. Additionally, the suggested system is computationally effective due to the application of machine learning and image processing.

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