PADDY AND MAIZE LEAF DISEASE DETECTION USING DEEP LEARNING

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***Abstract*:** An automatic method for spotting early disease and nutritional deficiencies in Paddy is shown in this project. maize and farming. In addition to providing food for people, agriculture also contributes significantly to a nation's economy. Every year, millions of dollars are spent on crop protection. Pests, nutritional deficiencies, plant diseases, and insects all cause crop damage and pose a serious threat to the crop's ability to flourish as a whole. Early disease identification and nutrition shortage detection are two ways to safeguard the crop. A timely study of the crop is the greatest approach to learn about its health. If disease or nutrition deficiency are discovered, necessary steps can be implemented to safeguard the crop from suffering a significant production loss in the long run. Early detection would be beneficial for reducing the use of pesticides and would offer suggestions for pesticide selection. Today, there is a lot of research being done worldwide in a wide range of fields for the autonomous diagnosis of diseases. The traditional technique of field inspection is with the naked eye, however it is exceedingly challenging to conduct a thorough inspection in big areas. Numerous human experts are required, who are very expensive and time-consuming, to evaluate the entire field. Therefore, a machine is needed that can both analyze the crops to look for infestation and classify the sort of illness on them. The photographs of leaves can be effectively analyzed using computer vision algorithms. Based on the characteristics of the photos Uses Support Vector Machine to classify images as having or not having disease. In comparison to other automated procedures, this one is easier and yields superior outcomes.

1. Introduction

Agriculture is the foundation of the Indian economy. Direct or indirect involvement in farming activities accounts for 50% of the population. This region produces a wide range of fruits, cereals, and vegetables that are sold to other nations. Therefore, it is essential to make goods of the highest quality with the highest output. The diagnosis of plant diseases is crucial in the realm of agriculture because plant illnesses cannot be prevented. Diseases can affect several portions of plants, including the fruits, stems, and leaves. Viral, fungal, and bacterial illnesses including Canker, bacterial spot, Alternaria, Anthracnose, etc. are the principal diseases that affect plants. Changes in the environment cause the viral disease, fungi cause the fungal disease, and bacteria cause the bacterial disease. Since it is possible to automatically identify automatic illnesses based on signs that appear on plant leaves detection of plant diseases is an important research area. Barbedo proposed a technique for automatically segmenting disease signs in plant leaf digital images that involves applying colour channel manipulation and Boolean operations to a pixels from a leaf binary mask.He suggested a method of manipulating the H and colour channel histograms to semi-automatically segment the symptoms of plant leaf disease. Pang et al. suggested using a local threshold and seeded region growing to automatically segment crop leaf spot disease photos. Singh and Misra suggested employing soft computing approaches for plant leaf disease detection. By using texture-based clustering for segmentation, Prasad et al. suggested an Unsupervised resolution-independent segmentation of natural plant leaf diseases. A method to segment leaves in images with non-uniform lighting was proposed by Du and Zhang and is based on genetics and maximal entropy algorithms (GA). Dhaygude and Kumbhar suggested employing image processing to identify agricultural plant leaf disease, where the texture statistics are calculated using spatial gray-level dependence matrices (SGDM). For the segmentation of plant disease spots, Diao et al. explored a variety of techniques, such as artificial neural network (ANN), edge-based, regional-based, etc. In the literature, various techniques for automatically segmenting leaves and identifying diseases have been suggested.

2. Scope of Project

Utilizing the right methods to distinguish between healthy and diseased leaves reduces crop loss and boosts productivity. This section includes various RCNN-Deep Learning algorithms that are currently in use to identify plant diseases. The majority of farmers are uneducated and underprivileged, which may lead to problems caused by animals and plant diseases that affect more than half of their crops. Additionally, it can be used in other disciplines of agricultural disease diagnosis in similar application settings.

2.1 Existing system and its issues

Early disease identification is a significant problem in agriculture research under the current system. Plant leaf illnesses have become a problem because they can significantly lower the output and quality of agricultural products. The primary strategy used in practice for the detection and identification of vegetable illnesses is the naked eye observation of experts. However, this necessitates ongoing expert supervision, which in large farms may be prohibitively expensive. Additionally, in some poor nations, farmers may need to travel great distances to see experts, which makes doing so both time- and money-consuming. Consequently, the system is unable to alert the person who should be informed about the bug in the leaf.

2.2 Literature Survey

In paper [1], the author focused on the application of deep multi-support vector machines and neural networks as hybrid machine learning algorithms to identify paddy leaf disease. Picture capture, image preprocessing, segmentation, and multi-support vector machine (MSVM) classification are the techniques utilized in the identification of leaf spot illnesses.

The author of study [2] concentrated on machine learning algorithms as SVM Classifier, Naive Bayes Classifier, and K-means Clustering as well as image processing approaches. In this study, image processing methods are employed to quickly and precisely identify cotton plant disease.

The author of study [3] concentrated on image processing methods and machine learning algorithms like SVM and K-means clustering that are utilized for identifying rice plant diseases.

In study [4], the author focused on the employing machine learning approaches, classifying illnesses of paddy plants as KNN Classifier, Bayes Classifier, and Support Vector Machines (SVM) classifiers. While the Bayes Classifier method only functions for offline data, KNN is fairly simple to implement.

Author of study [5] concentrated on Color Slicing Technique for Paddy Plant Leaf Blast Disease Detection via Automation Edge detection in this Color Slicing Technique has superior performance to conventional edge detection.

In study [6], the author concentrated on disease detection and classification using machine learning algorithms such the Nave Bayes Classifier. The rice plant disease can be found more quickly and effectively with this algorithm technique.

In paper [7], the author concentrated on the classification and detection methods of Decision Tree, Naive Bayes, and Logistic Regression.

The author of Paper [8] puts out the concept of leaf detection utilizing leaf photos. Machine learning and image processing techniques are used to recognize these images.

In study [9], the author focused on the use of machine learning methods such SVM and K Nearest Neighbor Classifiers to identify the disease affecting rice plants. This algorithmic technique is used to quickly and precisely identify rice plant diseases.

In paper[10], the author focuses on applying an Optimized Fuzzy Inference System to identify and categorize paddy leaf diseases. The median filter, texture feature, and color feature are used to process the photos of the paddy leaves that have been discovered.

In paper[11], the author focuses on algorithms that leverage Support Vector Machines (SVM) for classification and detection. Plant diseases like bacterial blight and brown spot are detected and categorized using the SVM algorithm.

Author of research [12] focused on recognizing and categorizing paddy leaf diseases utilizing Jaya algorithm and an optimized deep neural network. The illnesses bacterial blight, brown spot, sheath rot, and blast are all detected using this approach.

The author of paper [13] concentrated on an image processing algorithm to identify rice leaves. For the detection and classification of diseases, classification algorithms including Random Forest, Logistic Model Trees, and Nave Bayes are utilized.

In study [14], the author focused on the detection and classification of rice plant disease using machine learning approaches, such as the convolutional neural network algorithm. The detection of rice leaves is covered in this essay's discussion of picture preprocessing, segmentation, feature extraction, feature selection, and classification algorithms.

The author of paper[15] concentrated on machine learning algorithms like convolutional neural networks (CNN). It is utilized for image super-resolution, and researchers have found that training deeper networks on the dataset is more challenging

3. System Overview

Using our technology, all of the aforementioned issues with the current system can be fixed.

3.1 R-CNN

What is R-CNN?

A type of machine learning model called R-CNN, also referred to as RCNN, is utilized for computer vision applications, particularly for object detection. Region-Based Convolutional Neural Network is known as R-CNN.

How does a R-CNN works?

The following picture illustrates the idea of a regional CNN (R-CNN). Bounding boxes are used to define object regions, to classify numerous picture regions into the specified category, convolutional networks are then tested separately on each Region of Interest (ROI). The RCNN architecture was designed to deal with image detection issues. Also based on the R-CNN architecture that was improved to generate Faster R-CNN is Mask R-CNN.

What is Faster R-CNN?

Region Proposal Network, a faster form of R-CNN designs with two steps (RPN). RPN is only a Neural Network that suggests various items that are present in a specific image. Quick R-CNN. Each candidate box is used to extract features using RoIPool (Region of Interest Pooling), and then classification and bounding-box regression are carried out. A tiny feature map can be extracted from each RoI in a detection using the RoIPool function. By using a Region Proposal Network and Fast R-CNN architecture to understand the attention mechanism, Faster R-CNN advances this stream. Since there is no need to continuously feed the convolutional neural network 2 000 region suggestions Fast R-CNN" runs quicker than R-CNN Instead, a feature map is produced from the convolution operation, which is only performed once per image. Additionally, A faster R-CNN is a finer version of R-CNN because it was created to increase computation speed (run R-CNN much faster).

Semantic Segmentation

Each pixel is divided into a predetermined set of categories using semantic segmentation, which does not distinguish among different object instances. To put it another way, semantic segmentation aims to recognize and group similar items into a single category at the pixel level. All things were grouped together, as shown in the photograph above (person). Because it separates the topics of the image from the background, semantic segmentation is also known as background.

Instance Segmentation

The process of correctly identifying every object in an image while also finely segmenting each instance is known as instance segmentation, also known as instance recognition. Thus, it combines object localization, object detection, and object classification. In other words, this kind of segmentation takes a step farther to clearly distinguish each object that is categorized as a comparable instance. All objects for instance segmentation are people, as demonstrated in the example image above, however throughout the segmentation process, each person is treated as a separate entity. Since semantic segmentation emphasize the subjects of the image rather than the background, it is often referred to as foreground segmentation.

3 System Design

3.1 System Architecture

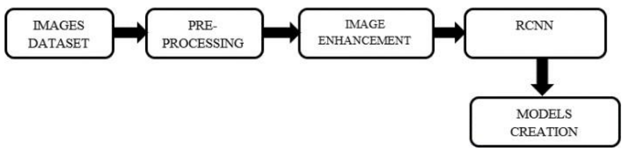


Figure 2: System Architecture

IMAGE PREPROCESSING:

The category of a given input fruit image in the dataset is determined using an image classification task. It is the fundamental undertaking in advanced picture comprehension and can be split into binary and multiple classification tasks. The output layer of an RCNN performs several convolution and pooling operations after which an image is categorized in accordance with the requirements. Between binary and multi classification tasks, there is just a variation in the activation function of the output layer. A high performance in natural image classification, including the usage of Region-based Convolution Neural Networks (RCNNs) in JPG/PNG image classification, can be achieved for the purpose of classifying fruit images so that the appropriate actions can be done to prevent the fruit from being produced.

IMAGE ENHANCEMENT:

The RGB image that was obtained is first transformed into grey. Now that our image is more contrasted with the backdrop, a suitable threshold level may be chosen for binary conversion. Image enhancing techniques are required here. The goal of image enhancement is to modify an image so that the final product is better suited for the intended application than the original image. The features of an image can be played with using a variety of techniques, though not always. Here are a few basic operations that are widely used to improve images.

FEATURE EXTRACTION:

A set of measured data is the starting point for the feature extraction process, which is used in Deep Learning, pattern recognition, and image processing to provide derived values (features) that are intended to be informative and non-redundant. This approach accelerates the processes of learning and generalization and, in some situations, improves the interpretations that people make. Dimension reduction and feature extraction go hand in hand. When an algorithm's input data is too big to review and deemed unnecessary, it might be reduced to a more manageable collection of attributes (also named a feature vector). Choosing the first features is a process known as feature selection. This reduced representation can carry out the intended task since it is predicted that the chosen features will include the relevant information from the input data.

DETECTING LEAF

Since it is a nice leaf, the leaf is one of the image's most prominent features. When it is running, the nice leaf must be located. Since the leaf is healthy, edges can be used for similar purposes. Once the thresholds are appropriately adjusted, canny edge detection is proven to produce very good results. Before edge detection, the image can be filtered to remove noise. There is a group of lines as a result of edge detection. The leaf must be taken out of it.

RCNN CLASSIFICATION

Based on geography Customized Convolutional Neural Networks for use in image and video recognition applications. Picture analysis tasks like segmentation, object detection, and image recognition are the principal applications for RCNN. The convolutional layer in a neural network connects the next hidden layer to each input neuron .The input layer's connections to the neuron hidden layer are limited to a narrow area. The feature map's dimensions are decreased by using a pooling layer. Inside the hidden layer of the RCNN, there will be several activation & pooling layers. The network's last tiers are known as Complete Layer Connectivity After being flattened, the output of the last pooling or convolutional layer is passed into the fully linked layer.

Workflow

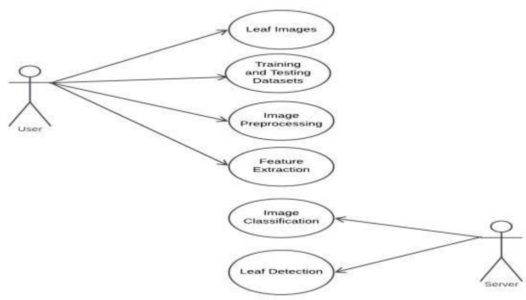
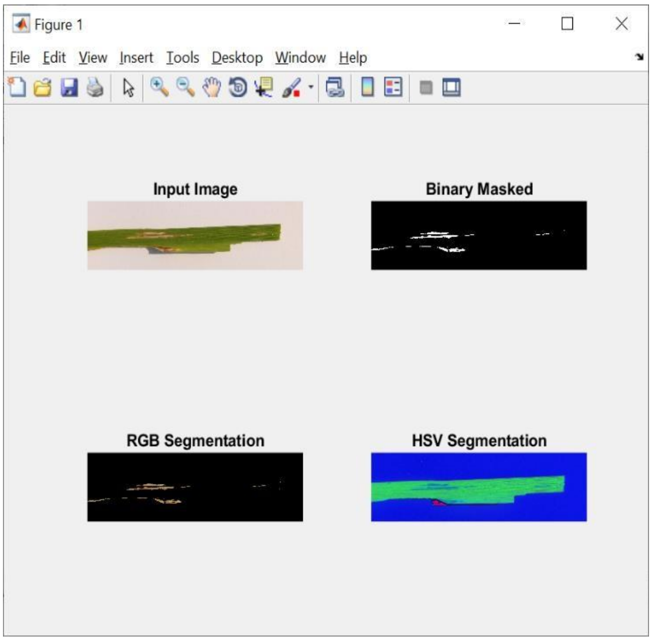
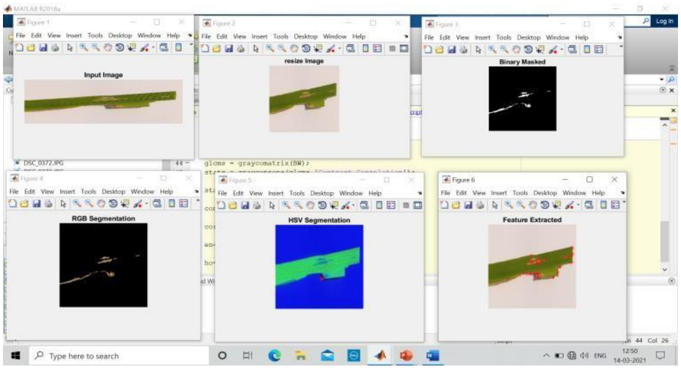


Figure 3: Workflow

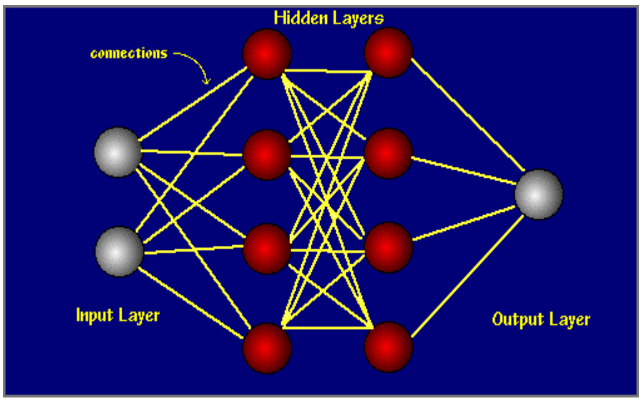
4.3 Execution and implementation



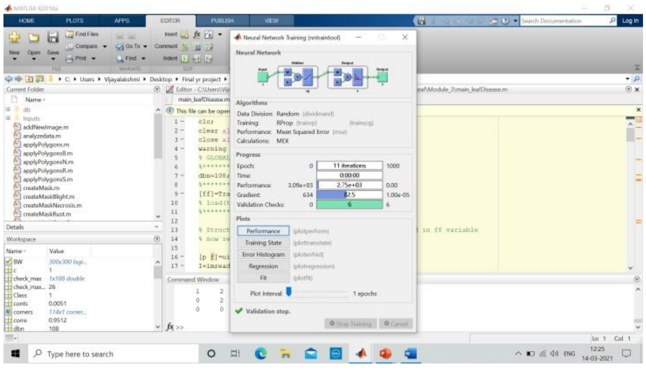
Module 2 – Segmentation



Module 3 – Classification

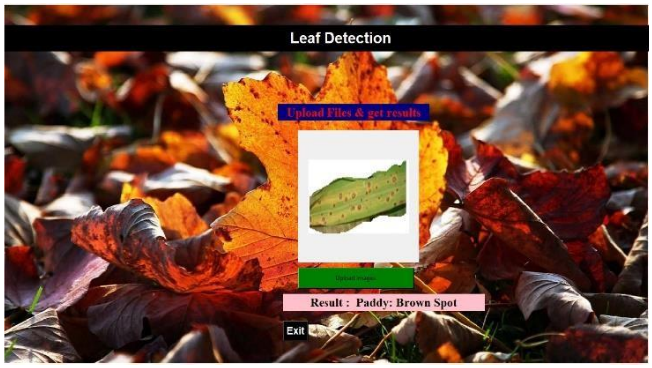


Deep RCNN Classification



Home Page

Paddy Leaf:



Maize Leaf:

Conclusion:

Using the MAT lab program, a system for diagnosing paddy illness has been created. To enhance and refine the image to a higher quality, image processing techniques are used. Additionally, bacterial leaf streak, leaf scald, brown spot, blast, leaf smut and bacterial leaf blight are classified according to paddy diseases using neural networks. Pre-processing, segmentation, analysis, and classification of the paddy illness are all part of the methodology. Before moving on to the binary conversion, every paddy test will first perform an RGB computation. Following that, all of the segmented paddy disease sample will be converted to binary data before being fed into a neural network for training and testing. The paddy diseases are therefore displayed by using the neural network technique. The sickness is finally defeated by the deep RCNN by showing the name of the fertilizer.

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