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CLAIMS IDENTIFIED AND CLASSIFIED FROM TREE LEAVES USING DEEP LEARNING

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ABSTRACT

Agriculture provides energy and a solution to global warming while feeding an ever-increasing population. Plant diseases are very significant since they can lower the quality and quantity of crops cultivated in agriculture. Early detection of plant diseases is crucial for curing and controlling the condition. The naked eye method is often used for diagnosing ailments. This technique involves experts who can recognize changes in leaf color. This process is labor-intensive, time-consuming, and unsuitable for large areas. Frequently, many specialists will identify the same ailment as a different one. This technology is expensive since it requires constant expert monitoring. Plant diseases can increase the cost of agricultural output and, if not treated promptly, can result in a producer's complete financial disaster. Producers must monitor their crops and spot early signs of plant illness to restrict disease spread at a low cost while saving the bulk of the product. Hiring skilled agriculturists can be expensive, especially in distant and isolated locations. Deep learning algorithms in photos can give an alternative method for plant monitoring, and a professional can administer such an approach to provide more affordable services. It includes feature extraction and classification and an image classification technique that employs a neural network algorithm to predict various illnesses. Also, expand the technique to incorporate pesticide recommendations depending on severity and data.

Index Terms— Plant disease prediction, Features extraction, Classification, pesticide recommendation, Neural network approach

INTRODUCTION

India is mostly an agricultural nation. Farmers can pick from a wide array of fruit and vegetable crops. The proven computational approach for identifying infections using infected images of various leaf patches is being enhanced by researchers. Images are recorded using a digital camera phone and processed with image growth software before being used in the leaf sport for training and testing classification. The system includes both image processing and powerful computing capabilities. Agriculture is the foundation of all countries. Agriculture research seeks to increase the quality and quantity of produce while lowering costs and improving profitability. Plant pests can degrade the quality of the agricultural product. Pathogens such as fungi, bacteria, and viruses cause these disorders. As a result, discovering and categorizing plant disease early on is a challenging task. Farmers require professional monitoring regularly, which may be prohibitively expensive and time-consuming. Depending on the presentation, a variety of ways have been proposed to solve or at least mitigate the issues utilizing image processing and various automatic categorization technologies.

• Image exploration may be used for the following purposes: Identify damaged leaves, stems, and fruits.
• Determine the disease-affected region.
• Identify the afflicted area's borders.
• Determine the hue of the pompous area.
• To determine the size and shape of the leaf.
• Identify the object accurately.

Disease control is a challenging task. The majority of infections occur on the plant's leaves or stems. Because of the intricacy of visual patterns, reliable quantification of visually detected diseases, pests, and features has yet to be investigated. As a result, there is a growing demand for more accurate and sophisticated visual pattern recognition. Different Types of Leaf Spot Diseases:

• Bacterial
• Fungal
• Viral

The vast majority of leaf ailments are caused by fungi, bacteria, and viruses. Fungi's reproductive structures are mostly determined by their form. Bacteria have shorter life cycles and are thought to be more basic than molds. With rare exceptions, bacteria exist as single cells that proliferate by splitting into two cells by binary fission. Viruses are extremely tiny particles composed of protein and genetic material that are not linked. A single biological science experiment can provide thousands of photos. Further studies, such as diagnosing lesions, analyzing quantitative aspects, calculating the area consumed by insects, and so on, may need photographs.

The vast majority of these operations are done by hand or using different software tools. It is not only a lot of effort, but it also has two major flaws: long processing periods and subjective opinions from different people. Plant scientists need powerful computer systems to automatically extract and evaluate relevant content to run a large number of experiments. Image processing is critical in this scenario. This study looks at image-processing approaches for analyzing leaf diseases.

RELATED WORK

Eisha Akanksha et al. [1] developed an efficient automated maize plant diagnostic system.The recommended approach includes four stages: preprocessing, feature extraction, classification, and segmentation. The photographs are first converted to RGB format, and any images included in the sounds are removed. The feature extraction stage is then assigned the R band. The classifier then utilizes the specified characteristics to assess whether a picture is normal or abnormal. Classification is performed using an optimized probabilistic neural network (OPNN). The artificial jelly optimization (AJO) technique is employed to enhance the PNN classifier. Finally, the leaf pictures of Northern leaf blight disease are processed by the segmentation stage, which isolates the diseased portion of the leaf. . The efficacy of the proposed lead illness categorization is evaluated using multiple quality indicators, including accuracy, sensitivity, and specificity.

Vibhor Kumar Vishnoi, et al. [2] focused on summarizing articles that merged soft computing with image processing concepts. As a result, the task of identifying plant illnesses using image processing techniques and soft computing has been separated into four modules: image capture, image pre-processing, image segmentation, and classification or identification. Before capturing and collecting images of desired plant parts such as leaves, roots, stems, and branches, various pre-processing techniques such as transformation, contrast stretching, scaling, rotation, smoothening, and others are used as needed; segmentation is then applied to extract the desired spotted/lesion regions from the infected original. Apart from that, feature sets are extracted from the segmented lesion region and used to train the classifier. During the testing process, the trained classifier evaluates if the illness in the test picture is infected or healthy. The test images go through the same steps as the train images, including pre-processing, segmentation, and feature extraction.

Anil A. Bharate, et al...[3] Patterns can be produced using a variety of methods, including spectroscopy and imaging technologies. Smart farming allows farmers to employ automated processes and technologies to combine knowledge, products, and services to increase output, quality, and yield. It helps farmers discover plant ailments early on and make prompt decisions, saving time and decreasing plant loss caused by diseases. Farmers will be0 able to discern between different fruit grades before marketing. The purpose of this article is to perform a survey on how to monitor plant diseases and provide improved solutions for enhanced yield and productivity. Many current systems include two image databases, one for querying and another for training. Several approaches have been used to detect illnesses in three fruits: apples, grapes, and pomegranates. This fungus affects just grapes and a few other closely related plants. It is the most prevalent disease to impact grapes. Powdery mildew appears as whitish or greenish powdery patches on the undersides of basal leaves. It also causes leaf curling, withering, and blotchy or distorted leaves in highly infected plants.

Jyotismita Khaki et al.,[4] Created automated plant cataloging systems to aid in the identification of plant species. In this regard, the present study proposes a novel plant recognition approach based on digital photos of plant leaves. People can recognize plants based on the form and texture of their leaves. These characteristics were represented using a set of computer-recognized features and data modeling techniques. Curvelet transform coefficients and Invariant Moments are employed to represent the geometry of the leaf, whereas Gabor filter outputs and metrics obtained from Gray Level Co-occurrence Matrices are used to represent the texture. The characteristics are then sent into two neural-based classifiers, which split them into a set of predetermined categories. To investigate optimum situations, experiments are done using qualities independently and in various combinations.

The author's methodology combines texture and form modeling techniques, which are regarded as crucial factors for discrimination. A complex Gabor filter (GF) and grey-level cooccurrence matrix (GLCM) are employed to capture the texture of a plant leaf, while curvelet transformations (CT) and invariant moments are utilized to record the leaf's shape (IM). However, the resultant feature values are influenced by the size and direction of the leaf picture.

Neeraj Kumar, et al.[5] aimed to significantly accelerate the laborious process of identifying, collecting, and monitoring plant species. Without visual identification tools such as Leafsnap, searching the many branches and infinite nodes of the taxonomic tree requires manually navigating a dichotomous key (decision tree). Answering hundreds of sometimes confusing questions, such as "Are the leaves at and thin?" might take many minutes or even hours to identify a single species using this approach. This is tough for experts; it is exceedingly difficult (if not impossible) for beginners. Untrained users attempt to capture leaves in situ, sometimes with intense lighting and blur artifacts, resulting in unprintable photos. Furthermore, many people picture stuff other than leaves. First, run a binary leaf/non-leaf classifier on all input pictures to answer both of these problems. If this classifier determines that an input image of a single leaf on a bright, untextured backdrop with no additional distractions is invalid, It alerts the user and directs them on how to capture an appropriate photograph. Then I realized that this simple technique was effective for training people without the need for long tutorials or help pages, which are often disregarded. It also reduces the computational strain on our system by excluding photographs that do not pass this categorization.

Naresh. Y.G, et al.…[6] It is critical to digitize valuable plant species and their information. This digitization is mostly based on photographs of plant leaves and other plant components such as fruits, flowers, and pollen grains, among others. As a result, there is a tremendous amount of digital data that has to be classified and retrieved. It is necessary to construct a computer vision system that can identify plant species utilizing their digital databases to give information to laypeople about medicinal plants. This study proposes a symbolic technique for identifying plant leaves using textural features. Textural information may be extracted from plant leaves using modified local binary patterns (MLBP). Plant leaves from the same species can have varying textures according to age, acquisition, and environmental circumstances. As a consequence, a large number of class representatives are picked using the clustering idea, and intra-cluster differences are recorded using interval-valued symbolic characteristics. The classification is simplified using a rudimentary nearest neighbor classifier. Extensive testing was performed on the newly created UoM medicinal plant collection, as well as the Flavia, Foliage, and Swedish plant leaf databases that are open to the public. The suggested methodology's findings are compared to those obtained using current methodologies. Even on this synthetic dataset, the Outex dataset is used for testing, and the results are positive.

Mónica G. Larese, et al.[7] The segmentation algorithm is built using unconstrained hit-or-miss transforms and adaptive thresholding. Several morphological characteristics from the segmented venation are calculated and identified using four distinct classifiers: support vector machines (linear and Gaussian kernels), penalized discriminant analysis, and random forests. The results are contrasted to those acquired from images of cleaned leaves, which require a more expensive, time-consuming, and sensitive collection technique. The findings are encouraging, indicating that the suggested technique is a more successful and cost-effective alternative to manual expert recognition. The saliency map of the model contains internal dynamics that generate attentional changes. As a result, this model gives a thorough explanation of bottom-up saliency, requiring no top-down direction to shift attention. This framework provides a massively parallel method for swiftly picking a limited number of interesting picture regions for subsequent examination using more complicated and time-consuming object-recognition techniques. In "guided search," feedback from higher cortical areas (for example, knowledge of goals to be found) was used to weigh the importance of various qualities, with only those with high weights able to reach higher processing levels.

EXISTING METHODOLOGY

Even though botanical categorization was not based on their characteristics, leaves are the most visible and often used technique of identifying tree species. They can be seen almost all year, are easy to photograph, and their forms have well-studied traits that allow, if not make, identification feasible. It serves as an instructive tool by employing high-level geometric criteria inspired by those used by botanists to categorize a leaf into a species list. Image quality will be enhanced by eliminating noise and other unwanted pixels, as well as extracting more information from the image. Image segmentation is a technique for studying pictures that may be used to categorize or cluster an image into several discontinuous pieces by grouping pixels to generate a homogenous area. Based on pixel properties such as gray level, color, texture, intensity, and others. The main purpose of the segmentation process is to learn more about the image and the region of interest, as well as to separate the item from the background. The parameters for segmenting a photograph are difficult to identify since they vary in each image and are also affected by the image's modal quality. Interactive procedures can be difficult and time-consuming in certain cases, while manual picture segmentation can be error-prone in others, and even completely automated approaches can make mistakes.

PROPOSED METHODOLOGY

Even when analyzing trees, leaves exhibit an astonishing variety of forms. However, it is necessary to build an accurate representation of what a leaf is that can accept practically any form of leaf. The fundamental form of a leaf is a significant factor in the identifying process. Botanists use several terms to describe the morphology of a simple leaf, the lobes of a palmate leaf, and the leaflets of a complex leaf. Because leaves may naturally have noncanonical, transitional forms, the boundaries between the various words are not well defined. The leaf's edge is also an important factor to consider. When trying to discriminate between two species with almost identical global morphologies, morphology can be critical. It might be composed of teeth of varied sizes and frequencies, clustered regularly or not, ranging from massive spiny points to little regular saw-like teeth to a smooth entire border. We provide a study on leaf image segmentation that is confined to semi-controlled settings, with leaves photographed against a solid light-colored background. Such photographs, by observing the various forms of the leaves, can be used to identify plant species. In this semi-controlled setting, we concentrate on segmentation, which gives us a more defined objective while also offering a variety of challenges. The diversity of leaf forms, the presence of shadows and specularities, and the time constraints imposed by interactive species identification applications are the most important of these.

In this project, we compare and contrast many prominent segmentation methods. Except for a few specialists, knowledge of plants, which used to be part of our immediate environment, has been lost in our more urbanized and artificial world. What is regarded as indisputable progress has also disseminated the names and usage of a huge variety of trees, flowers, and plants. However, as the belief in the need to protect plant resources and variety grows, so does the desire to reconnect with nature. And making it accessible for everyone who feels the need to identify a plant species, and research its history, and attributes is as much a method of passing lost information as it is a way of allowing people to see nature's incredible diversity. The identification of species is the first and most significant step in understanding the plant environment. Botanists have traditionally classified species based on the appearance and composition of fruits, flowers, and leaves. However, in the context of a broad non-specialist application, the most reasonable and widely used method in image processing is the use of leaves, which are available almost all year, are simple to shoot, and are easier to analyze from two-dimensional pictures. The recovery of a precise contour is a tough and crucial issue in the process of identifying trees from images of leaves in natural settings. For basic and lobed tree leaves, we provide an approach for overcoming the hurdles given by such complex pictures. The Active Contour method is used to extract features before driving the evolution of leaf borders. The polygonal model's global shape descriptors are used with local curvature-based features to classify the leaves across leaf datasets. Also, employ a categorization system to categorize ailments and deliver nutrients to affected leaves.

The classification technique employs a back propagation neural network approach to improve sickness classification accuracy and recommend leaf disease using multiclass classification. The suggested arrangement is seen in Figure 2.

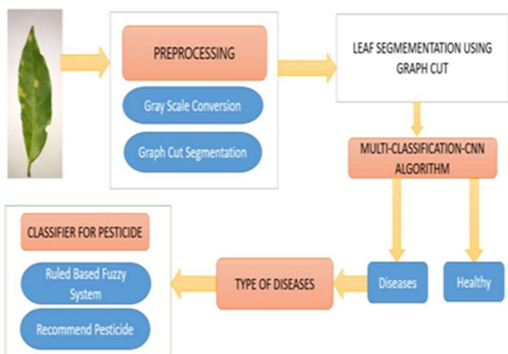


IMAGE ACQUISITION AND PRE-PROCESSING

Leaves are photosynthesis-specialized structures that are positioned on trees to optimize exposure to light while avoiding shading one another. We may add leaf pictures from the databases to this module. The LEAF database was created to test the ability to recognize wood species based on the form of their leaves. It comprises leaves from native, invasive, and imported species that survive in the Czech Republic, such as trees and shrubs (only foreign species found in parks are included). A single species' sample count (leaves) ranges from 2 to 25, for a total of 795 in the database. The leaves were scanned at 300 dpi, binarized, and preprocessed (denoising and cleaning) before being saved as PNG images.

This module converts an RGB picture to a grayscale. Because the color feature has limited dependability, the colors of leaves are always green tints, notwithstanding the diversity of changes in the atmosphere. As a result, the incoming RGB leaf image will be converted to a grey scale before pre-processing to identify unique plants based on their leaves. The equation is the formula for converting RGB pixel values to their greyscale equivalents.

Gray = 0.2989 * R + 0.5870 * G + 0.1140 * B, where R, G, and B represent the color of the pixel, respectively.

Next, use filtering techniques to eliminate the noise from the photographs. The filter's objective is to eliminate noise from the image that has warped it. It follows a statistical technique. Filters are often designed with a certain frequency response in mind. Filtering is a nonlinear image processing approach for reducing "salt and pepper" noise. When it comes to minimizing noise while preserving edges, a median filter outperforms convolution. Additionally, picture binarization jobs should be implemented.

IMAGE SEGMENTATION

This module allows us to employ the active contour approach with automatic descriptors. Unconstrained active contours applied to the delicate natural imagery we're working with would result in unacceptable contours that sought to squeeze through every fissure and aw in the leaf's border. The strategy we suggest is to use the polygonal model developed in the first step not only as an initial leaf contour, but also as a shape prior, guiding the model's evolution toward the real leaf border. To drive the evolution of an active contour, use the generated polygon as a shape. Then, set the initial contour on a contracted version of the polygon and constrain the contour to stay close to it.

$E(\tau) = \alpha ELeaf(\tau) + \beta EShape(\tau) + \gamma EGradient(\tau) + \delta ESmooth(\tau) - \delta EBalloon(\tau)$ for a contour τ outlining an area $\Omega(\tau)$

We chose to retain the previous phase's dissimilarity map rather than adding an external energy factor based on color consistency or distance to a mean since we already had an efficient measure of how well a pixel should fit in the leaf in terms of color.

DISEASE PREDICTION

Bacteria, fungi, viruses, and other insects all harm the leaves. The back propagation neural network approach is used in this module to identify the leaf picture as normal or impacted. Vectors are constructed based on leaf features such as color, shape, and textures. The preprocessed leaves can then be classified using layers with conditions. With the use of a multiclass classifier, we can more accurately forecast illnesses in tomato leaf photos. Steps in CNN algorithms: Step 1: Randomly initialize the weights and biases. Step 2: feed the training sample. Step 3: Propagate the inputs forward; compute the net input and output of each unit in the hidden and output layers. Step 4: backpropagate the error to the hidden layer.Step 5: update weights and biases to reflect the propagated errors. Training and learning functions are mathematical procedures used to automatically adjust the network's weights and biases. Step 6: terminating condition.

PESTICIDES RECOMMENDATION

Bacteria, fungi, viruses, and other insects all damage the leaves. The back propagation neural network technique is employed in this module to determine if the leaf image is normal or affected. Vectors are created by combining leaf attributes like color, shape, and texture. The preprocessed leaves can then be categorized using conditional layers. We can use a multiclass classifier to better predict diseases in tomato leaf pictures.

EXPERIMENTAL RESULTS

Real-time datasets were utilized in this chapter. This framework utilized feature extraction and classification algorithms. The performance may then be evaluated based on accuracy measures. The accuracy measure is calculated as:

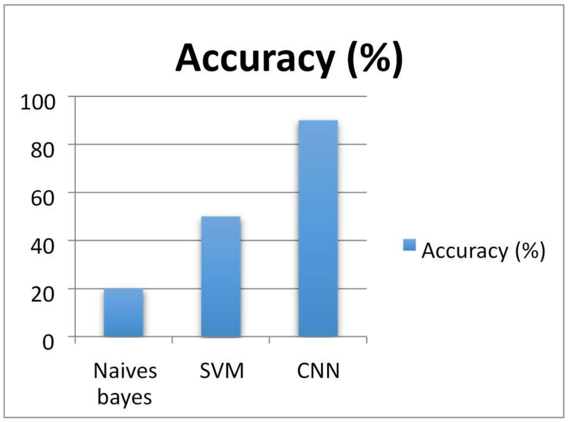
Accuracy=(TP+TN /TP+TN+FP+FN) *100

The suggested approach delivers a higher accuracy rate than machine learning algorithms.

Algorithm	Accuracy (%)
NaiveBayes	20
SVM	50

CNN	90

Table (1) Accuracy table



The performance chart shows that CNN outperforms previous machine-learning algorithms in terms of accuracy.

CONCLUSION

In this paper, we look at the many techniques and algorithms for segmentation and classification approaches that have been created to improve segmentation accuracy. However, the findings show that, when compared to the proposed graph cut model, segmentation approaches perform poorly and are difficult to implement in large datasets. We developed a method for segmenting a leaf in a natural image by optimizing a polygonal leaf model used as a shape before a precise leaf boundary using a convolutional neural network methodology. It also provides a set of global geometric descriptors that, when combined with local curvature-based features extracted from the final contour, allow tree species classification.The segmentation approach is based on a color model that is insensitive to illumination variations. However, if the color alone does not appropriately characterize the leaves, a global color model for the entire image may be insufficient. Finally, employ a neural network classification approach to classify leaf diseases into three types: bacteria, fungi, and viruses. The pesticides should then be administered to the afflicted leaves according to the measurements.

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