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VIDARBHA REGION CROPS DISEASE IDENTIFICATION: A COMPARATIVE APPROACH

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Abstract: Agribusiness is one of the significant callings in numerous nations including India. Vidarbha is one of the regions from Maharashtra India where cotton, maize (corn) jowar, tomato, rice Soyabean are common crops . The scientific classification and distinguishing proof of yield contamination got a lot of significance in specialized as well as monetary in the Agricultural Industry. While monitoring infections in plants with the assistance of experts can be expensive in farming region. Plant sicknesses can influence immense produce of harvests representing a significant threat to food security. To keep away from this gamble, a methodology is required which performs early finding, ailing in abundant pieces of the globe because of the deficiency of fundamental framework. This paper talks about a few investigations and comparison of various methods performed for plant illness recognition. Each arrangement of strategies enjoys its own benefits, constraints and the boundaries influencing the outcomes. This paper plans to get a top to bottom comprehension of calculation choice and key difficulties looked in took on approaches. Utilizing this investigation, we have compared various strategies that can be utilized in various phases of a plant sickness discovery framework to give the best outcomes at each stage and recognized key difficulties that can be looked during identification.
Keywords: Deep Learning, Neural Networks, Image pro- cessing, CNN, Plant Disease, SVM,GNN

Introduction: Plant illnesses can influence the entire produce, which makes early finding and order essential. This helps save assets, time, and cash and takes on ideal preventive measures to stay away from the hardship later on. To recognize impacted regions on plant leaves, two significant methodologies can be followed. The principal approach is Image Processing by applying different methods: sifting, grouping, histogram exam- ination among numerous others, to track down the locale of interest. The locale of interest can really establish the harmed piece of the leaf and the shape and estimate examination can identify the illness that is besetting the plant. Picture handling calculations are straightforward and the utilization of Python libraries, for example, OpenCV, simplifies uses of these strategies. In any case, in these calculations, the normal precision of infection identification is not extremely high [25]. The other methodology is Deep Learning where a profound brain network engineering can be applied to prepare and test on the information base. The most known brain network design to be utilized for pictures is the convolutional brain organization (CNN). A CNN comprises of convolutional layers, regularly layered with a maximum pooling layer, which are trailed by at least one completely associated layers. The loads utilized for include choice along with not entirely set in stone during the preparation period, which assists with saving memory prerequisites and computational intricacy. The CNN takes in input pictures and in view of the loads doled out to its hubs can arrange the kind of sickness that is available on the leaf. The exactness accomplished can be high however; there are various cons to this methodology: the computational intricacy, even with CNN, can be very high. Knowing the district of interest might chop down extensive calculation time and increment the precision of the framework. Consequently, we observed that the methodologies worked the best when utilized together. The picture handling a piece of as far as possible the part that should be broke down, generally speaking improves the pictures for better grouping and afterward passes it on the profound learning engineering. Table 1 gives a concise outline of the methods examined and crop inclusion in the plant sickness location space and their accessibility in right now accessible audit papers. In our paper, we have consolidated a relative report to comprehend various methods utilized for each progression of an overall plant infection recognition framework.

1. Related Work:

Gouse et al(2022)[2] proposed five mod- els achieved the VGG16 98.43%, VGG19 98.65%, InceptionV4 98.57, ResNet-50 98.57% model to identify diseases in rice leaf images with a transfer learning tech- nique. Using these model parameters, the final proposed VVIR model accurately classified objects with a accuracy of 98.80%.Arathi et al.(2023)[1] used deep learning technique, CNN is employed for feature extraction which is used to detect plant diseases.The Experimental results achieved showed that the proposed model i.e., DenseNet-121 pre-trained Model is capable of classifying different leaf images in the dataset with higher classification accuracy of 91%.Dulhare et al(2022)[3] taken the help of Convolutional neural network (CNN) which is a deep learning technique used to solve computer vision issues such as image classification, object segmentation, image analysis, etc. In the proposed five models achieved the VGG16 98.43%, VGG19 98.65%, InceptionV4 98.57, ResNet-50 98.57% model to identify diseases in rice leaf images with a transfer learning technique. Using these model parameters, the final proposed VVIR model accurately classified objects with a accuracy of 98.80%.

2. General Flow in Methodology:

This segment gives a relative inside and out investigation of calculations used in each progression of the overall stream. This overall stream (Fig 1) is planned with seven stages most normally utilized in plant sickness discovery

A. *Input Leaf Image*

The datasets incorporate both ailing and sound leaves of harvest. We separated the accessible datasets based on the quantity of harvests, to be specific, single yield and various yields. Table 2 is a plain correlation between the datasets [2, 3, 4] in view of the harvests accessible, number of yield pictures, illness covered, technique for plant leaf picture catch and limits of the relating dataset. We have additionally concentrated on the normal leaf infections in the overviewed papers to get their side effects and the dataset including them. Table 1 orders the infections comprehensively as indicated by the primary sickness class, for example, parasitic, bacterial, shape, viral and mite affected and afterward examines the sub- classifications.

B. *Preprocessing*

This is a significant stage prior to dissecting the picture as it assists remove with any noising present in the information picture via doing activities at the most minimal deliberation level. In the event that best in class calculations are applied prior to eliminating commotion, it might prompt undesirable outcomes. Table 2 gives an outline of the different preprocessing strategies, their benefits and impediments

C. *Segmentation*

This procedure is helpful in separating the pictures into a few sections or sets of pixels. The thought is that somewhere around one section will have the district of interest (ROI) which can be used for additional complex calculations. Here our ROI is the sick part. Table 5 gives a short outline of the different division procedures like K-Means, thresholding, Automated and K-Medoids

D. *Disease Detection*

In the wake of getting the fragmented workmanship from the prior advance, the subsequent stage is to break down the infected part and to distinguish the most plausible sickness

E. *Feature Extraction*

To recognize the likelihood of illness it is critical to investigate specific elements. The most well-known highlights removed from a leaf picture are shading, surface, shape, size of spots on them, and so forth The procedures utilized are: Histogram preprocessing, CNN, Automated Script, Gray

Level Co-event Methodology or Spatial Gray Level Dependence Matrix. In Histogram strategies, the normal highlights removed are shading and surface. When grayscale pictures are utilized to separate highlights, it is genuinely helpful to involve CNN rather than histogram extraction as histogram approaches will quite often sum up pixel values to limit values. Mechanized Script is like both histogram and CNN approaches in managing shading and extraction values. It was noticed that the Histogram and Automated Script methods are only used to remove the shading highlight. Dim Level Co-event Methodology (GLCM), then again consolidates a factual way to deal with depict the shape include by dark level testing though Spatial Gray-level Dependence Matrices (SGDM) separates highlights like difference, energy, nearby homogeneity and relationship from the HUE part. The use of GLCM and SGDM together is worthwhile for grayscale as well as shaded pictures and covers most elements. Table 6 outlines the utilization of these procedures in different paper.

F. .Feature Selection

When the elements are removed, not all highlights con- tribute similarly to infection identification. To eliminate information overt repetitiveness, it is indispensable to choose just those highlights, which can alone add to the component vector regardless give a decent exactness. Each component enjoys specific benefits and burdens concerning sickness location on leaves

3. Challenges and Future Scope:

We have distinguished a portion of the significant difficulties - both extraneous like catch conditions and natural like infection varieties, to investigate top to bottom their causes and their effect on the presentation of the procedures examined up to this point. Our point is to beaten these difficulties and take out their unfavorable impacts in our proposed approach from here on out. The difficulties are as per the following:

a) The goal of camera should be suitable with the goal that the nature of leaf picture is not compromised.

b) Influence of environment while taking pictures can change the enlightenment spots, which could influence the location calculation.

c) The side effects delivered by various infections might be the same and they might be available at the same time, prompting fluffy arrangement rather than fresh.

d) Size of the dataset should be adequately enormous to productively prepare the model for testing powerfully without expanding processing time.

e) Appropriate pre-handling methods to keep away from clamor impedance at infection location stage.

f) Deciding the division of preparing and testing information to stay away from overfitting and under fitting.

g) Most of the datasets accessible are nation or district explicit. To work with plants from different nations or districts, crude pictures from the fields must be taken, named and afterward handled. Marking the various infections is conceivable just under master watch.

h) Different channels turn out best for various infections, Ex: Otsu channel gives best outcomes for Bacterial sicknesses. In this way, picking the right arrangement of channels is vital.

i) Recently, Graph Neural Networks (GNN) have emerged as a potent tool in understanding relational data samples [18, 19]. GNNs, when applied to agricultural datasets, showed promise in deciphering intricate relationships, especially in understanding plant phenology and structure [20, 21, 22] sets. However, their application in disease classification, especially in conjunction with recurrent neural architectures, remains nascent.

4. Conclusion

In this paper, we have talked about the requirement for a framework to recognize and order plant sickness upheld by factual boundaries. Besides, we have checked on different examination papers in light of the overall stream followed by plant infection recognition frameworks like information leaf, pre-handling, division, illness location, include extraction, highlight choice, order as sound or unhealthy, execution measures and exactness included. We likewise contrasted our review paper and existing overview papers to assist with distinguishing the exploration holes and work on them further. Through this study, we have distinguished key procedures required at each stage and strategies that are generally utilized inside each stage. The different picture handling procedures can be joined along with various learning networks and classifiers with the recent approach of Machine learning to create ideal outcomes, particularly when the information is boisterous.

Table 1. Several Methods on selected crops in various research papers

Methods/Crops Covered		[25]	[23]	[24]	[24]	[25]	[23]	[23]	[7-11]
	K-Means	C#	C#	C#	C#	C#	C#	C#	
Methods of Classifications	Support Vector Machine	C#	C#	C#	C#	C#	C#		
	Neural Networks	C#	C#	C#	C#	C#	C#	C#	
	Deep Convolutional Neural Networks				C#				
	Learning Vector Quantization								
	Graph Based Neural Network								C#
Crops Covered	Rice	C#	C#			C#		C#	C#
	Orange								C#
	Soybean						C#		
	Maize					C#			C#
	Potato					C#			
	Tomato				C#	C#			
	Cotton			C#		C#		C#	C#

C#- This Techniques are Covered in mentioned research Paper

Table 2. Comparison of Features

Dataset	**Crops**	**Images**	**Disease Identified**
Maize/Corn Dataset [23]	Maize/Corn	18,422	Bacterial leaf blight
Rice Dataset [24]	Rice	55	Bacterial leaf blight, Brown spots, Leaf Smuts
PlantVillage Dataset [25]	Orange, Soybean, Maize, , Potato, Tomato	55,509	Fungal Infection, blight, mold, viral, mite- disease
Cotton Dataset [25]	Cotton	1030	Alternaria-macrospora, . Bacterial Blight

Table 3. Kinds of Infections and Various Symptoms available

Infection Category		**Various Pathogens**	**Visible Symptoms**	**Dataset 1 [23]**	**Dataset 2 [24]**	**Datase t 3 [25]**
Fungal	Corn	Cercospora zeae-Maydis	Dark leaf spots encompassed by a yellow corona which become sporadic or broadened pale-earthy colored streaks.			C**
		Maydis Puccinia sorghi	Round pustules, fine, brown becoming brown-dark as the plant develops.			C**
		Exserohilum turcicum	Stogie formed or circular necrotic dim green injuries on the leaves.	C**		C**
	Potato	Alternaria solani	Dull injuries with yellow line which might shape concentric rings of raised and indented tissue on the leaves.			C**
	Tomato	Alternaria solani	Oval molded sores with a yellow chlorotic district across the injury.			C**
		Septoria Leafspot	Water-doused spots or round grayish-white spots on the underside of more established leaves			C**
		Corynespora Cassiicola-sac fungus	Little, pinpoint, water-drenched spots on the leaf.			C**
		FULVFU	Haphazardly divided, diffuse light green or yellowish spots.			C**
Bacterial	Orange	Candidatus Liberibacter	Yellowing of one appendage or one area of shade, yellowing of leaf veins; messy mottling as well as green islands (spots) encompassed by totally yellow leaf tissue.			C**
	Tomato	Vesicatoria	Little water-splashed spots.			C**
	Rice	Bacterial Blight	Yellow-orange stripes on leaf cutting edge.		C**	C**
		Brown Spot	Spots on the leaf		C**	C**
		Leaf Smuts	Dark Spores, vigorously contaminated leaves become yellow, and the leaf tips pass on and become dim.		C**	C**
Mold	Potato	Phytophthora Infestans	Sporangiophores on the outer layer of the leaves.			C**
	Tomato	Phytophthora Infestans	Leaves become yellow and may become twisted and disfigured			C**
Viral	Tomato	Yellow Curl Virus	Leaves become decreased in size, twist up, seem folded and show yellowing of veins and leaf edges.			C**
		Mosaic Virus	Dark green mottling			C**
Mite-Affected	Tomato	Tetranychus urticae	Leaves become bronzed or silvery.			C**

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C**- This Images are available in mentioned datasets

Table 4. Comparison of Different Preprocessing Methods

Methods	**Removal of Image Background**	**Conversion of Color Space**	**Various Filtering Algorithms**
Methods	Determination of binary mask for selection of ROI followed by addition of the image obtained in the last step and original image to eliminate background. Hence removing remaining white spaces by cropping. [24]	Rgb to L*ab color space conversion [24]. Rgb to gray-scale conversion [24] Resizing and then converting Rgb image to gray-scale image. [23]	Replacing every pixel value with the median of the local intensity
Benefits	Intently looks like human insight and has major areas of strength for a towards decent division results. [24]	This gives better parting of data about chrominance and a variety space free of device. [24]	Filters viz. median filter helps to remove salt-pepper noise. [24]
Drawbacks	Sudden Lightning Change can't be detected	Rgb color space is sensitive to non- uniform illumination; L*ab color space has problem of singularity.	The kind of filter to be utilized is well defined for the sort of noise in the image. With the erroneous filter, image parameters could be changed

Table 5. Comparison between various segmentation methods

Methods	K-Means Clustering	Threshold based segmentation	K-Medoids Clustering	Automated Segmentation
Brief Explanation	Centroids are recalculated after each sum of distance calculation. Tri partitioning corresponding to various parts of leaf. To get clusters corresponding to various color, texture and shape [23].	Thresholding based on otsu's method deals with iterating through all the possible threshold values and finds a measure of location for the pixel levels each side of the threshold [24] [25].	Random select for initial medoids which will randomly select non-medoids object. Cost is computed for swapping and if the cost is negative then perform the swap operation [24].	Segmentation is done by the help of a script.
Benefits	Iterative K-Means diminishes the amount of distance esteem by reassigning each pixel to its nearest neighbor [24].	Detect diseases having a significant color symptom [24].	More vigorous as compared to K-Means. Less impacted by frames and other outrageous qualities	Tuned nicely to work with Plant Village dataset [23].
Drawbacks	Difficult to choose the specific k value for Image dataset	Fails with disease having large color variations	Obtains different results for different runs on the same set of Images.	Low robustness and high intricacy of execution

Table 6. Types of Methods available for Feature extraction

Research Paper No.	**[24]**	**[24]**	**[23]**	**[24]**	**[25]**	**[23]**
Techniques :	Image Histogram: The Features extracted are color and texture	CNN: The context based information is extracted such as color of leaves	Features extracted are color, shape and texture	GLCM#: In this method gray level sampling is used to describe the features. SGDM##:The HUE component is used to extract local homogeneity and correlation.	CNN: Performed include extraction of variety for both full-variety and dark scale approach	Automated Script: variety, delicacy and immersion values extricated

GLCM#: Grey Level Co-Occurrence Methodology; SGDM##: Spatial Grey Level Dependence Matrices

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