Creation and Segmentation of image dataset of Mung bean plant leaf

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Abstract- Automated plant disease identification is an enduring research subject. Leaves are available for most of the season and they have a flat (2d) surface that's why practically it is physible to detect disease symptoms using image analysis. Data collection and pre-processing are the most significant and crucial stages to obtain the data that can be taken as accurate and appropriate for further processing. Machine learning techniques require a large amount of data for training. The present paper focuses on process standardization for the creation of an image dataset of Mung bean plant leaves and preprocessing steps to enhanced captured images. The diseases in leaves result in loss of economic, and production status in the agricultural industry worldwide. The identification of disease in leaves using image processing, reduce the reliance on the farmers for the safeguard of agricultural crops. In this paper creation and segmentation process of Mung bean plant leaf, performed. Present Dataset will be available to be used by researchers to save their time, efforts, and cost related to dataset creation. Segmentation of images will intensify the accuracy of the identification of various diseases.

Keywords— Mung bean Leaf, Leaf, Images, Dataset, Preprocessing, Segmentation, GrabCut

I. INTRODUCTION

Pulses play important role in nutritional requirements. Pulses help to reduce inanition among the poor masses. They provide minerals, vitamins, energy, dietary fiber, the protein required for the health condition. Pulses contain substantial amounts of essential nutrients like calcium, iron, and lysine (Gowda et al 2013). Latest research studies suggested that consumption of pulses may have likely health benefits as well as reduced risk of hypertension, gastrointestinal disorders, cardiovascular diseases, cancer, diabetes, and osteoporosis (Jacobs and Gallaher 2004).

(Gaston & O'Neill, 2004) projected possibility of plant species identification using artificial intelligence and digital image processing techniques. Ever since many studies have proposed various methods for automated plant and plant disease identification. (Rzanny, Seeland, Wäldchen, & Mäder, 2017a) explored many approaches for image acquisition and pre-processing to improve the quality of plant organ images to train classifiers for the classification process. This paper proposes an image dataset of Mung bean plant leaves to carry out an image-based plant disease identification and classification. There are no standard plant leaves image dataset for Mung bean leaves is available. The database is created manually by capturing mung leaves images using various smart mobile phones in a controlled environment. How leaf images are acquired and pre-processed does have a substantial effect on the accuracy of the classifier trained on them..

II. LITERATURE REVIEW:

Various effective and novel methods have been projected in recent times for the automatic identification of plant and plant organ diseases. Methods are exploring visual cues present in almost all of those parts, like fruits (Aleixos N, 2002) (Corkidi G, 2005) (López-García F, 2010), stems, roots (Smith SE, 1991), kernels (Ahmad IS, 1999), and leaves. (Amruta Ambatkar et al., 2017) proposed a method for rose diseases detection using an 8-connected boundary detection algorithm for edge detection. (Sannakki et al., 2012) compared binary morphology and Sobel edge detector algorithms that detect edges and proved that morphology is more effective compared to others. (Sabu, Sreekumar & Nair, 2017) used HoG (Histogram of oriented Gradients) and SURF (Speeded Up Robust Features) together with a k-NN classifier to identify plants. (Wang et al. 2013) aimed at a new algorithm that segments a single leaf from real-time video and achieved clear and accurate edges. (Kumar, Surya & Gopi, 2017), conducted the research that considered both front and backside of leaves with fresh and dried leaves and extracts features and test them using Support Vector Machine (SVM) and Multi-Layered Perceptron (MLP) classifiers. (Dahigaonkar & Kalyane, 2018) done related work by extracting various features including geometric, texture, shape, and color using SVM Classifier. (Nisale et al. 2011) achieve 93% accuracy by extracting geometric features of a leaf for detecting various stages and deficiencies in the plant. (Arivazhagan et al. 2013) proposed an algorithm that detects and classify an unhealthy region of leaves and segmented only diseased region with the help of an SVM classifier and obtained 94.74% accuracy. (Venkataraman & Mangayarkarasi, 2017) performs classification and identification of plants using various statistical parameters, texture features, and SVM. (Aitwadkar, Deshpande & Savant, 2018) used Artificial Neural Network (ANN) for automatic identification of plants. (Batvia, Patel & Vasant, 2017) used Convolution Neural Network (CNN) for automatic identification of plants.

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(Ali et al., 2017)	Citrus	Color &	199	Leaf	Bagged Tree	Custom (DSLR Camera)	99.9%
		Texture			Classifier		
(Tippannavar et	Brinjal,	Color	500	Leaf	KNN, PNN	Custom (Digital Camera)	75.04%
al., 2017)	Broad bean,						71.24%
	Cucumber,						
	ridge guard,						
	Spinach &						
	tomato						
(Kaur et al.,	Multi-	GLCM	NA	Leaf	SVM	NA	95.16 -
2017)	Species	Features					98.38%
(Mondal et al.,	Okra &	Texture	79(Okra)	Leaf	Naives	Custom (Digital Camera)	NA
2017)	Bitter		75(Bitter		Bayes		
	gourd		gourd)		Classifier		
(Ma et al., 2017)	Cucumber	Color	93	Leaf	Color map	Custom (Digital Camera)	NA
(Al-Otaibi et al.,	Basil &	Statistical	30	Leaf	NN	Custom (Digital Camera)	80%
2017)	Parsley	Feature					
(Manimegalai et	Apple	GLCM	NA	Leaf	SVM	NA	98.46%
al., 2017)		Features					
(Chouhan et al.,	Plant Leaf	Region	276	Leaf	NN	Existing (Plant Village)	86.21%
2018)		Growing					
(Zhang et al.,	Apple &	Color	150 (Apple)	Leaf	k-means	Custom	90.43%
2018)	Cucumber		150				(Apple)
			(Cucumber)				92.15%
							(Cucumber
(Picon et al.,	Wheat	Color	8178	Leaf	Deep	Custom (Mobile Phones)	>98%
2018)					Convolution		
(Junior et al.,	Multi-	Shape	600	Leaf	RNN	NA	88.92%
2018)	Species						
(Sunny et al.,	Citrus	Texture	100	Leaf	SVM	Custom (Digital Camera)	NA
2018)							
(Nababa et al.,	Oil Palm	Probability	NA	Leaf	Naïve Bayes	NA	80%
2018)		Function					
(Fuentes et al.,	Tomato	Color	5000	Leaf	NN	Custom (Digital Camera)	96%
2018)							
(Sabu et al.,	Multi-	SURF,	200	Leaf	kNN	Custom	NA
2017)	Species	HOG					
(Vijayashree &	Multi-	Texture	127	Leaf	Dissimilarity	Custom	NA
Gopal, 2017)	Species						
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(Pushpa, Anand	Multi-	Shape &	208	Leaf	NA	Custom	93.75%
& Nambiar,	Species	Edge					
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(Kumar &	Multi-	Shape,	500	Leaf	Unique ID	Custom	NA
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(Kumar, Surya	Multi-	Color &	1200	Leaf	SVM	Custom (Scanned Images)	94%
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(Dahigaonkar &	Multi-	Color,	128	Leaf	SVM	Custom	96.66%
(Danigaonkar & Kalyane, 2018)	Species	Texture &	120	Leai	5 4 141	Custom	50.00%
Karyane, 2018)		Shape					
		Shape					

(Venkataraman &	Multi- Species	Texture	260	Leaf	SVM	Custom	NA
Mangayarkarasi,							
2017)							
(Aitwadkar,	Multi-	Edge,	50	Leaf	ANN	Custom	75%
Deshpande &	Species	Color					
Savant, 2018)							
(Batvia, Patel &	Multi-	Shape	4000	Leaf	CNN	Custom	NA
Vasant, 2017)	Species		approx.				
(Venkataraman	NA	Shape	5	Leaf	ANN, SVM	Custom	NA
&							
Mangayarkarasi,							
2016)							
(Arun &	Multi	Color &	250	Leaf	SVM	Custom (Digital camera)	98.7%
Christopher	Species	Texture					
Durairaj, 2017)							

Used Abbreviations; SVM: Support Vector Machine, ANN: Artificial Neural Networks, PNN: Probabilistic Neural Networks, KNN: k-nearest neighbors, CNN: convolutional neural network.

Table 1 summarizes the researches carried out in recent times

A detailed study of the research work done during the last few years on leaf images are summarized in Table 1. From the information presented in Table 1 main point noticeable is, researches in the field of plant disease identification mostly focuses on a single plant organ leaf. Also, the researchers are forming a custom dataset for their research work as there is no standard dataset available for Mung bean plant organs. The abbreviations used are summarized in the last row of Table 1. Below mentioned Table 2 contains a list of some existing plant image datasets.

Dataset	Organ	No. of Species	Culture	No. of Images
Flavia	Leaf	32	Multi- Species	1907
Plantvillage	Leaf	3	Bell Paper, Potato, Tomato	15442
Oxford_flower102	Flower	102	Flowers	7000+
Swedish	Leaf	15	15 tree classes	1125
New Plant Disease	Leaf	14	Fruits & Vegetables	87000
Coffee-dataset	Leaf	1	Coffee	1747 a plant image dataset

Table 2Existing plant image datasets

The main point to note in Table 2 is that none of the above plant organ image datasets are dedicated to the Mung bean plant leaf organ. This research addresses the need for a benchmark dataset for Mung beanplant organs.

III. MATERIALS AND METHODS

A. Dataset Collection

The crucial necessity for accurate plant disease identification is a standard dataset of plant organ images. The dataset creation consists of stages as follows:

- Plant Selection
- Capturing Images
- Dataset Creation.

For this research, the Mung bean plant is under consideration as it is a local crop of the South Gujarat Region. In the present work, the leaf dataset consists of four types of healthy and diseased Mung bean leaf images; these are Cercospora Leaf Spot, Yellow Mosaic Virus, and Powdery Mildew. These were collected from The Navsari Agriculture University at Navsari, Gujarat, India for reflective study. A pictorial assessment of the above-mentioned study site is shown in Fig. 1.



Fig. 1. Study Site of Mung bean Plants

Leaf samples are acquired indoor to minimize the effect of lighting conditions. Leaves were digitally captured in a controlled environment using Oppo A5 13MP and MI Note 8 Pro 64MP smartphones.

The Database consists of 1500+ images which include 400+ healthy and 1000+ diseased leaves. The diseases considered are Cercospora Leaf Spot, Powdery Mildew, and Yellow Mosaic Virus. Fig. 2 represents the healthy and diseased Mung bean leaves.



Fig. 2. Healthy & Diseased Mung Bean Leaves

B. System Model and Discussion

The system model is consist of four crucial steps as follows:

1) Pre-processing: Pre-processing helps to bring out useful information from an image.

2) Segmentation: Segmentation is used for locating objects in the image and to detect bounding lines of the image, background subtraction.

3) Feature extraction: In this phase, unique characteristics of an object or group of objects are collected.

4) Classification: Classification is the phase where training and testing take place. It is where the decision takes place using features extracted from the previous phase.

From the above four phases first, two phases have been discussed in detail in the following sub-sections and the remaining two phases will be implemented in the future. For implementation, OpenCV an open-source computer vision library with Python is used.

a) Pre-processing: Afterimage acquisition the preprocessing phase takes place. In this phase, image enhancement will be done. For this various operations are carried out in a series: RGB image Acquisition and color transformation, normalization/ resize of image size, Augmentation, masking green pixels, Segmentation. This phase makes changes in the image and makes it appropriate for segmentation.

Resize an image

Resizing refers to the scaling of an image. It helps to reduce or increase no of pixels from an image. Fig. 3 represents the image resize phase.

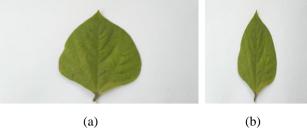


Fig. 3. (a) Original Image, (b) resized image

Augmentation

Augmentation encompasses a wide range of techniques used to generate new training samples from the original ones. It helps us to increase the size of the Dataset for training. Image augmentation artificially creates training images through a combination of multiple transformations. The result of image augmentation is displayed in Fig. 4.

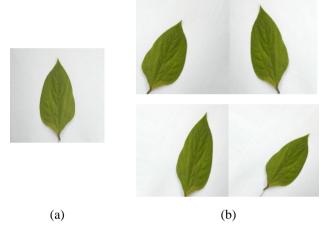


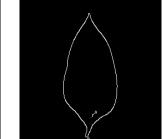
Fig. 4. (a) Original Image, (b) Augmented images

b) Segmentation: Image segmentation is the first step in image analysis and pattern recognition it is a critical and essential step and is one of the most difficult tasks in image processing, as it determines the quality of the final result of the analysis (Jagtap et al., 2014). During the segmentation phase, the image will be divided into several segments so that the analysis process becomes easy. In this study, edge detection is performed using the canny() edge detector and Interactive foreground extraction is performed using Grebcut() algorithm. Fig. 5 depicts the edge detection and Fig. 6 depicts the Foreground extraction process.



(a)



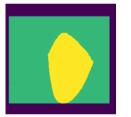


(b) Fig. 5. (a) Original images, (b) Extraction of Boundary

Steps for segmentation



(a) Input Image





(b) Simple masked image



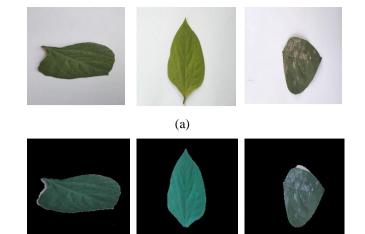
(c) separate foreground and background



(e) Output image after masking

Fig. 6. Segmentation Process

The GrabCut algorithm segments object from the background in an image. The user has to mark a rectangular area as the primary input. The outer part of this rectangle is considered as background and pixels in the outside area are considered as known background and inside are unknown background. A model is then created using this data, to find out whether the unknown pixels are foreground or background. Fig. 7 represents some of the segmented images.



(b)

Fig. 7. (a) Original Images, (b) Segmented Images

GrabCut is one of the extensively used algorithms for removing background in images. The automatic GrabCut technique was experimentally tested using a dataset of Mung bean leaf images as shown in Fig. 7. This work can be used in regions like plant leaf image classification, plant leaf disease detection from plant leaf images.

IV. CONCLUSION

We considered the creation of the Mung bean plant organ image dataset. Dataset will be released to be used by researchers to save their time, efforts, and cost associated with dataset creation. Segmentation of the image will increase the accuracy of identification of healthy and diseased pixels.

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(d) final mask image

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