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 pre-processing 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, Pre-processing, 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.

Researchers	Culture	Primary Feature	No. of Images Considered	Plant Organ	Classifier / Techniques	Image Acquisition / Dataset	Accuracy
(R. P. Narmadha & G.Arulvadivu)	Paddy	Shape, Color	NA	Leaf	K-means	Custom (Smartphones or digital camera)	NA
(Hidayatuloh et al., 2018)	Tomato	Color	1400	Leaf	CNN	Custom (Smart Phone)	86.92%
(Kawacher Ahmed et al., 2019)	Rice	Color	480	Leaf	Decision Tree	Existing ("Rice leaf diseases data set." https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases.)	97.91%
(V. N. T. Le et al., 2019)	Canola radish & Barley	Texture	30000	Leaf	SVM	Custom (On-Semi VITA 2000 camera sensor)	91.85%
(Sridhathan C. et al., 2018)	Multi-Species	Color	NA	Leaf	K-mean	Custom (Digital camera or Mobile Phone)	98.27%
(G. Dhingra et al., 2019)	Basil	Color	400	Leaf	SVM	Custom (EOS 5D Mark III, 22.3 megapixel CMOS sensor)	98%
(G. Saleem et al., 2019)	Multi-Species	Color	1600 625	Leaf	KNN	Existing (Flavia) Custom	97.6% 96.1%
(Y. Sun, 2019)	Tea Plant	Texture	1308	Leaf	SVM	Custom (digital SLR camera)	98.5%
(S. Sivasakthi, 2020)	Greenhouse Crop	Color, Texture	NA	Leaf	SVM, ANN	Custom (Camera)	92% 87%
(Majid et al., 2013)	Rice	Color	NA	Leaf	PNN	Custom	91.46%
(Arvind et al., 2018)	Maize	Texture	2000	Leaf	Multiclass SVM	Existing (Plant Village)	83.7%
(Suryawati et al., 2018)	Tomato	Color	18160	Leaf	CNN	Existing (Plant Village)	94%
(Suresha et al., 2017)	Rice	Color	NA	Leaf	kNN	Custom (Digital Camera)	76.59%
(Saradhambal. G et al., 2018)	Multi-Species	Color	75	Leaf	k-means	Custom	NA
(Tucker et al., 1997)	Sunflower & Oat	Shape	40	Leaf	Thresholding	Custom (TMC-76 color CCD)	NA
(Zhang et al., 2011)	Citrus	Color, Texture	500	Leaf	AdaBoost	Custom (DigitalCamera)	88%
(Wang et al., 2012)	Wheat & Grape	Color, Texture & Shape	185	Leaf	PNN	Custom (Digital Camera)	94.29%
(Zhang et al., 2016)	Cucumber	Color	100	Leaf	SVM	Custom	92% Approx.
(Quin et al., 2016)	Alfalfa	Color, Texture & Shape	899	Leaf	SVM	Custom (Digital Camera)	80% Approx.
(Dey et al., 2016)	Betel Vine	Color	12	Leaf	Otsu	Custom	NA
(Youssef et al., 2016)	Vegetable Crop	Color, Texture & Shape	284	Leaf	SVM	Custom (Digital Camera)	87.805

(Ali et al., 2017)	Citrus	Color & Texture	199	Leaf	Bagged Tree Classifier	Custom (DSLR Camera)	99.9%
(Tippannavar et al., 2017)	Brinjal, Broad bean, Cucumber, ridge guard, Spinach & tomato	Color	500	Leaf	KNN, PNN	Custom (Digital Camera)	75.04% 71.24%
(Kaur et al., 2017)	Multi-Species	GLCM Features	NA	Leaf	SVM	NA	95.16 – 98.38%
(Mondal et al., 2017)	Okra & Bitter gourd	Texture	79(Okra) 75(Bitter gourd)	Leaf	Naives Bayes Classifier	Custom (Digital Camera)	NA
(Ma et al., 2017)	Cucumber	Color	93	Leaf	Color map	Custom (Digital Camera)	NA
(Al-Otaibi et al., 2017)	Basil & Parsley	Statistical Feature	30	Leaf	NN	Custom (Digital Camera)	80%
(Manimegalai et al., 2017)	Apple	GLCM Features	NA	Leaf	SVM	NA	98.46%
(Chouhan et al., 2018)	Plant Leaf	Region Growing	276	Leaf	NN	Existing (Plant Village)	86.21%
(Zhang et al., 2018)	Apple & Cucumber	Color	150 (Apple) 150 (Cucumber)	Leaf	k-means	Custom	90.43% (Apple) 92.15% (Cucumber)
(Picon et al., 2018)	Wheat	Color	8178	Leaf	Deep Convolution	Custom (Mobile Phones)	>98%
(Junior et al., 2018)	Multi-Species	Shape	600	Leaf	RNN	NA	88.92%
(Sunny et al., 2018)	Citrus	Texture	100	Leaf	SVM	Custom (Digital Camera)	NA
(Nababa et al., 2018)	Oil Palm	Probability Function	NA	Leaf	Naïve Bayes	NA	80%
(Fuentes et al., 2018)	Tomato	Color	5000	Leaf	NN	Custom (Digital Camera)	96%
(Sabu et al., 2017)	Multi-Species	SURF, HOG	200	Leaf	kNN	Custom	NA
(Vijayashree & Gopal, 2017)	Multi-Species	Texture	127	Leaf	Dissimilarity	Custom	NA
(Pushpa, Anand & Nambiar, 2016)	Multi-Species	Shape & Edge	208	Leaf	NA	Custom	93.75%
(Kumar & Talasila, 2014)	Multi-Species	Shape, Texture & Color	500	Leaf	Unique ID	Custom	NA
(Kumar, Surya & Gopi, 2017)	Multi-Species	Color & Texture	1200	Leaf	SVM	Custom (Scanned Images)	94%
(Dahigaonkar & Kalyane, 2018)	Multi-Species	Color, Texture & Shape	128	Leaf	SVM	Custom	96.66%

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

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

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 pre-processing 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

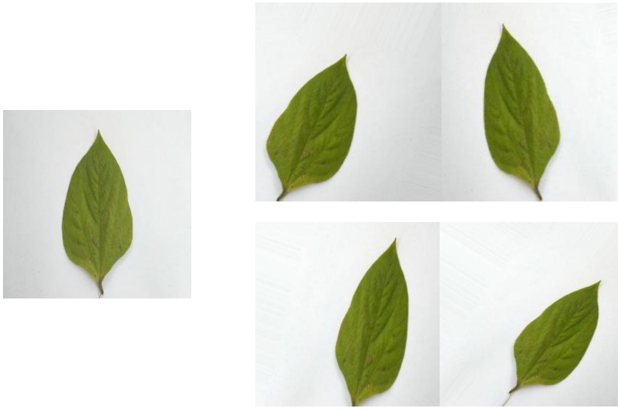
Resizing refers to the scaling of an image. It helps to reduce or increase no of pixels from an image. Fig. 3 represents the image resize phase.

(a) (b)

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.

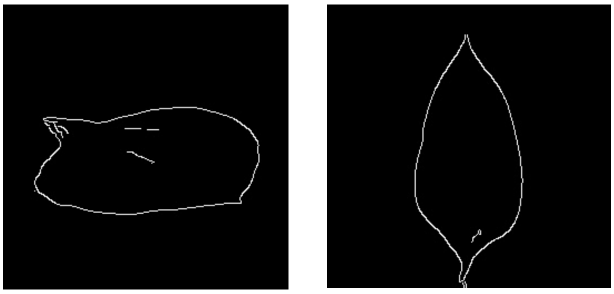


(a) (b)

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)

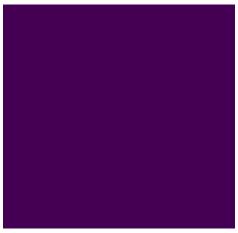


(b)

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

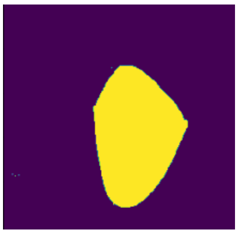
Steps for segmentation

(a) Input Image

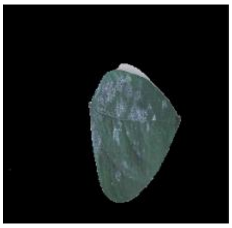


(b) Simple masked image

(c) separate foreground and background



(d) final mask image



(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.

(a)

(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.

References

[1] A.F. Fuentes, S. Yoon, J. Lee, D.S. Park, High-performance deep neural network-based tomato plant diseases and pests diagnosis system with a refinement filter bank, Front. Plant Sci. 9 (2018).

[2] Ahmad IS, R. J. (1999). Color classifier for symptomatic soybean seeds using image processing. Plant Disease, 83(4), 320-327.

[3] Aitwadkar, P. P., Deshpande, S. C., & Savant, A.V. (2018). Identification of Indian medicinal plant by using artificial neural network. International Research Journal of Engineering and Technology, 5(4),1669–1671.

[4] Aitwadkar, P. P., Deshpande, S. C., & Savant, A.V. (2018). Identification of Indian medicinal plant by using artificial neural network. International Research Journal of Engineering and Technology, 5(4),1669–1671.

[5] Akbar Hidayatuloh, M. N. (October 22-25, 2018). Identification of Tomato Plant Diseases by Leaf Image Using Squeezenet Model. International Conference on Information Technology Systems and Innovation (ICITSI) Bandung - Padang.

[6] Aleixos N, B. J. (2002). Multispectral inspection of citrus in real-time using machine vision and digital signal processors. Comput Electron Agric, 33(2), 121-137.

[7] Amruta Ambatkar, Ashwini Bhandekar, Avanti Tawale, Chetna Vairagade, and Ketaki Kotamkar, “Leaf Disease Detection using Image Processing”, Proceedings of International Conference on Recent Trends in Engineering Science and Technology, Vol. 5, pp. 333 -336, 2017.

[8] Arun, C., & Christopher Durairaj, D. (2017). Identifying Medicinal Plant Leaves using Textures and Optimal Colour Spaces Channel. Jurnal Ilmu Komputer dan Informasi, 10(1), 19-28. doi:http://dx.doi.org/10.21609/jiki.v10i1.405

[9] Batvia, V., Patel, D., & Vasant, A. R. (2017). A Survey on Ayurvedic Medicine Classification using Tensor flow. International Journal of Computer Trends and Technology, 53(2), 68-70.

[10] Batvia, V., Patel, D., & Vasant, A. R. (2017). A Survey on Ayurvedic Medicine Classification using Tensor flow. International Journal of Computer Trends and Technology, 53(2), 68-70.

[11] C.C. Tucker, S. Chakraborty, Quantitative assessment of lesion characteristics and disease severity using digital image processing, J. Phytopathol. 145 (7) (1997) 273–278.

[12] Corkidi G, B.-R. K.-C. (2005). Assessing mango anthracnose using a new three-dimensional image-analysis technique to quantify lesions on fruit. Plant Pathol, 55(2), 250-257.

[13] D. Mondal, D.K. Kole, K. Roy, Gradation of yellow mosaic virus disease of okra and bitter gourd based on entropy-based binning and Naive Bayes classifier after identification of leaves, Comput. Electron. Agric. 142 (2017) 485–493.

[14] Dahigaonkar, T., & Kalyane, R. (2018). Identification of Ayurvedic Medicinal Plants by Image Processing of leaf samples. International Research Journal of Engineering and Technology, 5(5), 351-355.

[15] Dahigaonkar, T., & Kalyane, R. (2018). Identification of Ayurvedic Medicinal Plants by Image Processing of leaf samples. International Research Journal of Engineering and Technology, 5(5), 351-355.

[16] Dr. Sridhathan C, D. M. (2018). Plant Infection Detection Using Image Processing. International Journal of Modern Engineering Research (IJMER), 8(7), 13-16.

[17] Endang Suryawati, Rika Sustika, R. Sandra Yuwana, Agus Subekti, Hilman F. Pardede, "Deep Structured Convolutional Neural Network for Tomato Diseases Detection," ICACSIS 2018 978-1-7281-0135-4/18/S31.00 ©2018 IEEE, 2018.

[18] F. Qin, D. Liu, B. Sun, L. Ruan, Z. Ma, H. Wang, Identification of alfalfa leaf diseases using image recognition Technology, PLoS ONE 11 (12) (2016) 1–26.

[19] G. Dhingra, V. K. (Mar-2019). A novel computer vision-based neutrosophic approach for leaf disease identification and classification. Measurement, 135, 782-794.

[20] G. Saleem, M. A. (Feb - 2019). Automated analysis of visual leaf shape features for plant classification. Comput. Electron. Agricult., 157, 270-280.

[21] Gaston, K. J., & O'Neill, M. A. (2004). Automated species identification: why not?. Phil. Trans. R. Soc. Lond. B,359, 655-667. http://doi.org/10.1098/rstb.2003.1442.

[22] Gowda C L L, Srinivasan S, Gaur P M and Saxena K B (2013) Enhancing the productivity and production of pulses in India. In: Shetty P. K., Ayyappan S and Swaminathan M. S. (eds.) Climate Change and Sustainable Food Security, Pp 63-76. National Institute of Advanced Studies, Bangalore and Indian Council of Agricultural Research, New Delhi.

[23] H. Ali, M.I. Lali, M.Z. Nawaz, M. Sharif, B.A. Saleem, Symptom-based automated detection of citrus diseases using color histogram and textural descriptors, Comput. Electron. Agric. 138 (2017) 92–104.

[24] H. Wang, G. Li, Z. Ma, X. Li, Image recognition of plant diseases based on principal component analysis and neural networks, in: Proceedings of the IEEE International Conference on Natural Computation (ICNC), 2012, pp. 246–251.

[25] J. Ma, K. Du, L. Zhang, F. Zheng, J. Chu, Z. Sun, A segmentation method for greenhouse vegetable foliar disease spots images using color information and region growing, Comput. Electron. Agric. 142 (2017) 110–117.

[26] J.J.D.M.S. Junior, A.R. Backes, O.M. Bruno, Randomized neural network-based descriptors for shape classification, Neurocomputing 312 (2018) 201–208.

[27] Jacobs D R and Gallaher D D (2004) Whole-grain intake and cardiovascular disease: A review. Current Atheroscler 6: 415-23.

[28] Jianlun Wang, Jianlei He, Yu Han, Chanqui Ouyang, and Daoliang Li, "An Adaptive Thresholding Algorithm of Field Leaf Image", Computers and Electronics in Agriculture, Vol. 96, pp. 23-39, 2013.

[29] K. Dey, M. Sharma, M. R. Meshram, Image processing based leaf rot disease, detection of betel vine (Piper BetleL.), in: Proceedings of the International Conference on Computational Modeling and Security (CMS), 2016, pp. 748–754.

[30] K. R. Arvind, P. Raja, K. V. Mukesh, R. Aniirudh, R. Ashiwin, Cezary Szczepanski, "Disease Classification in Maize crop using a bag of features and multiclass support vector machine," in Proceedings of the Second International Conference on Inventive Systems and Control (ICISC 2018) IEEE Xplore Compliant - Part Number: CFP18J06-ART, ISBN:978-1-5386-0807-4; DVD Part Number: CFP18J06DVD, ISBN: 978-1-5386-0806-7.

[31] Kawcher Ahmed, T. R. (2019). Rice leaf disease detection using machine learning techniques. International Conference on Sustainable Technologies for Industry 4.0 (STI), IEEE, (pp. 1-5). Dhaka, Bangladesh: IEEE.

[32] Kholis Majid, Y. H. (28-29 Sep 2013). "I-PEDIA: Mobile Application for Paddy Disease Identification using Fuzzy Entropy and Probabilistic Neural Network". ICACSIS (pp. 403-406). IEEE.

[33] Kumar, M. P., Surya, C. M., & Gopi, V. P. (2017). Identification of ayurvedic medicinal plants by image processing of leaf samples. Third International Conference on Research in Computational Intelligence and Communication Networks, 231-238.

[34] Kumar, M. P., Surya, C. M., & Gopi, V. P. (2017). Identification of ayurvedic medicinal plants by image processing of leaf samples. Third International Conference on Research in Computational Intelligence and Communication Networks, 231-238.

[35] Kumar, S. E. & Talasila, V. (2014). Leaf features-based approach for automated identification of medicinal plants. International Conference on Communication and Signal Processing, 210-214. doi:10.1109/ICCSP.2014.6949830

[36] López-García F, A.-G. G. (2010). Automatic detection of skin defects in citrus fruits using a multivariate image analysis approach. Comput Electron Agric, 71(2), 189–197.

[37] M. Nababa, Y. Laia, D. Sitanggang, O. Sihombing, E. Indra, S. Siregar, W. Purba, R. Mancur, The diagnose of oil palm disease using naive bayes method based on expert system technology, J. Phys. Conf. Ser. 1007 (1) (2018) 1–5.

[38] M. Zhang, Q. Meng, Automatic citrus canker detection from leaf images captured in the field, Pattern Recog. Lett. 32 (15) (2011) 2036–2046.

[39] M.B. AL-Otaibi, A.S. Ashour, N. Dey, R. Abdullah, A. A. AL-Nufaei, S. Fuqian, Statistical image analysis based automated leaves classification, in: Proceedings of the 2nd International Conference on Information Technology and Intelligent Transportation Systems (ITITS), 2017, vol. 296, pp. 469.

[40] P. Kaur, S. Singla, S. Singh, Detection and classification of leaf diseases using an integrated approach of support vector machine and particle swarm optimization, Int. J. Adv. Appl. Sci. 4 (8) (2017) 79–83

[41] Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild, Comput. Electron Agric (2018).

[42] Pushpa, B. R., Anand.,C., & Nambiar Mithun, P. (2016). Ayurvedic Plant Species Recognition using Statistical Parameters on Leaf Images. International Journal of Applied Engineering Research, 11(7), 5142-5147

[43] R.P.Narmadha, G. (Jan. 05 – 07, 2017). Detection and Measurement of Paddy Leaf Disease Symptoms using Image Processing. . International Conference on Computer Communication and Informatics (ICCCI - 2017), Coimbatore, INDIA.

[44] S. Arivazhagan, R. Newlin Shebiah, S. Ananthi, and S. Vishnu Varthini, "Detection of Unhealthy Region of Plant Leaves and Classification of Plant Diseases using Texture Features", Agricultural Engineering International: CIGR Journal, Vol. 15, No. 1, pp. 211-217, 2013.

[45] S. M. Hambarde, Sachin B. Jagtap, "Agricultural Plant Leaf Disease Detection and Diagnosis Using Image processing Based on Morphological Feature Extraction," IOSR Journal of VLSI and Signal Processing (IOSR-JVSP), vol. 4, no. 5, sep-2014.

[46] S. Manimegalai, G. Sivakamasundari, Apple leaf diseases identification using support vector machine, in: Proceedings of the International Conference on Emerging Trends in Applications of Computing (ICETAC), 2017, pp. 1–4.

[47] S. S. Chouhan, A. Kaul, U. P. Singh, S. Jain, Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards Plant Pathology, IEEE Access 6 (2018) pp. 8852–8863.

[48] S. Sunny, M.P.I. Gandhi, An efficient citrus canker detection method based on contrast limited adaptive histogram equalization enhancement, Int. J. Applied Engg. Res. 13 (1) (2018) 809–815.

[49] S. Tippannavar, S. Soma, A machine learning system for recognition of vegetable plant and classification of abnormality using leaf texture analysis, Int. J. Sci. Eng. Res. 8 (6) (2017) 1558–1563.

[50] S. Zhang, H. Wang, W. Huang, Z. You, Plant diseased leaf segmentation and recognition by fusion of superpixel K-means and PHOG, Optik 157 (2018) 866–872.

[51] S. Zhang, Z. Wang, Cucumber disease recognition based on Global-Local Singular value decomposition, Neurocomputing 205 (2016) 341–348.

[52] S.Sivasakthi, PLANT LEAF DISEASE IDENTIFICATION USING IMAGE PROCESSING AND SVM, ANN CLASSIFIER METHODS. International Conference on Artificial Intelligence and Machine learning. Journal of Analysis and Computation (JAC).

[53] Sabu, A., Sreekumar, K., & Nair, R. (2017). Recognition of ayurvedic medicinal plants from leaves: A computer vision approach. Fourth International Conference on Image Information Processing, 574-578.

[54] Sabu, A., Sreekumar, K., & Nair, R. (2017). Recognition of ayurvedic medicinal plants from leaves: A computer vision approach. Fourth International Conference on Image Information Processing, 574-578.

[55] Sanjeev S Sannakki, Vijay S Rajpurohit and Sagar J Birje, “Comparison of Different Leaf Edge Detection Algorithms using Fuzzy Mathematical Morphology”, International Journal of Innovations in Engineering and Technology, Vol. 1, No. 2, pp. 15-21, 2012.

[56] Saradhambal G, Dhivya R., Latha S., R. Rajesh, "Plant disease detection and its solution using image classification", International Journal of Pure and Applied Mathematics, vol. 119, no. 14, 2018

[57] Smith SE, D. S. (1991). Quantification of active vascular-arbuscular mycorrhizal infection using image analysis and other techniques. Australian Journal of plant physiology, 18(6), 637-648.

[58] Sumeet S. Nisale, Chandan J. Bharambe, and Vidva N. More, “Detection and Analysis of Deficiencies in Groundnut Plant using Geometric Moments, Proceedings of World Academy of Science, Engineering and Technology, Vol. 5, pp. 512-516, 2011.

[59] Suresha M, Shreekanth K N, Thirumalesh B V, "Recognition of Diseases in Paddy Leaves Using kNN Classifier," in 2nd International Conference for Convergence in Technology (I2CT), 2017.

[60] V. N. T. Le, B. A. (2019). Effective plant discrimination based on the combination of local binary pattern operators and multi-class support vector machine methods. Inf. Process. Agricult., 6, 116-131.

[61] Venkataraman, D., & Mangayarkarasi, N. (2016). Computer vision based feature extraction of leaves for identification of medicinal values of plants. IEEE International Conference on Computational Intelligence and Computing Research, 1-5.

[62] Venkataraman, D., & Mangayarkarasi, N. (2017). Support vector machine-based classification of medicinal plants using leaf features. International Conference on Advances in Computing, Communications, and Informatics, 793-798.

[63] Venkataraman, D., & Mangayarkarasi, N. (2017). Support vector machine-based classification of medicinal plants using leaf features. International Conference on Advances in Computing, Communications and Informatics, 793-798.

[64] Vijayashree, T., & Gopal, A. (2017). Leaf identification for the extraction of medicinal qualities using image processing algorithm. International Conference on Intelligent Computing and Control, Coimbatore, 1-4. doi:10.1109/I2C2.2017.8321884

[65] Y. Es-saady, I. El Massi, M. El Yassa, D. Mammass, A. Benazoun, Automatic recognition of plant leaf diseases based on a serial combination of two SVM classifiers, in: Proceedings of the Second International Conference on Electrical and Information Technologies (ICEIT), 2016, pp. 561–566.

[66] Y. Sun, Z. J. (2019). SLIC_SVM based leaf diseases saliency map extraction of the tea plant. Comput. Electron. Agricult, 157, 102-109.

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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 is 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

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