Bibliography

Sr. No	Participation	Title	Organizing Institutions/Industry / University	Month & Year
1	Research Methodology Course (Online/Offline)	Understanding Research Methods	Coursera	Apr-19
2	Workshop / STTP	Machine Learning And Deep Learning using python	DUIAS AND DSIM&C, GUJCOST, DST	Jan-20
3	FDP (Faculty Development Program)	Structural Equation Modeling	Atmiya University, Rajkot	Dec-19
4	E-Quiz	Teacher/Researcher Category Of India's First Ever IPR Olympiad 2019	ISERD INDIA	Sep-19
5	Online Course	LaTex101x :LaTex for students, Engineers, and Scientists	IIT BOMBAY	Sep-19
6	Online Course	Python for Data Science	Congnitive Class	Dec-19
7	Workshop / STTP	Basics of Machine Learning	CRSTES, IISER Bhopal, NPTEL, IIT Madras	Apr-20
8	Webinar	Data Science using Machine Learning from Scratch	CESA, Indus University	Dec-19
9	Webinar	Effective Ways to Develop E_Content	SMT.Devkiba Mohansinhji Chauhan College Of Commerce and Science (affiliated to uni. Of Mumbai)	May-20
10	Webinar	Challenges for Research Paper Writing & Publishing	SMT. K.S.N Kansagara Mahila Arts & Commerce College, Rajkot	May-20
11	Webinar	Predective model using Deep learning, Data science, Importance of	V.S.Patel College - Bilimora, BCA department	May-20

		cyber security in digital world		
12	Webinar	How to Publish high quality technical journal paper	IEEE	Apr-20
13	Webinar	IEEE Xplore Digital Library : Supporting Every Aspect of YOUR career	IEEE	Apr-20
14	Webinar	IEEE Xplore Digital Library : Supporting Every Aspect of YOUR career	IEEE	Apr-20
15	Webinar	Research Ethics	NPTEL	May-20
16	Webinar	Understanding the usefulness of Turnitin	Atmiya University, Rajkot	Jun-20
17	Online Course	Build Your First Android App (Project-Centered Course)	Coursera	Mar-20
18	FDP (Faculty Development Program)	Online Faculty Development Programme On R Language	Auxillium College,Vellore (TN) and Spoken Tutorial IIT Bombay	May-20
19	FDP (Faculty Development Program)	Evolution From Offline to Online Teaching	Satish Pradhan Dhyanasadhna College Thane, Dept. Of IT-Uni. Of Mumbai and Microsoft	Jun-20
20	Online Course	Data Science : Supervised Learning in Python	Udemy	Feb-20
21	Online Course	Machine Learning Using Python	Udemy	Jun-20
22	Online Course	Support Vector Machines with Scikit-Learn	Coursera	Aug-20

Appendix A

Plagiarism Report

Ouriginal

Document Information

Analyzed document	1_190881001_CS_AkrutiNaik_Thesis.pdf (D144497966)
Submitted	9/21/2022 9:40:00 AM
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Sources included in the report

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Entire Document

DESIGN AND DEVELOPMENT OF A MODEL TO CLASSIFY CROP FOLIAR DISEASES
A Thesis Submitted to the Atmiya University, For the Degree of Doctor of Philosophy in COMPUTER SCIENCE
by Akruti Narendrakumar Naik Enrolment No. 190881001 Under the Guidance of Dr.
Hetal R. Thaker Department of Computer Science ATMIYA UNIVERSITY, Yogidham Gurukul, Kalawad Road, Rajkot–360005, Gujarat (India) August, 2022
Page | I Declaration by the Candidate I declare that thesis entitled "Design and Development of a Model to Classify Crop Foliar Diseases" is my own work conducted under the supervision of Dr. Hetal R. Thaker at Department of Computer Science, Faculty of Science, Atmiya University, Rajkot, Gujarat, India and approved by the Director of Research. I further declare that to the best of my knowledge the thesis does not
contain any part of any work which has been submitted for award of any degree either in this University or any other University without proper citation. Date: Place: Akruti Narendrakumar Naik

Appendix B

Publications

Appendix – A (International Journals)

[1] Naik, A., Thaker, H., & Vyas, D. (2021). A survey on various image processing techniques and machine learning models to detect, quantify and classify leaf plant disease. Proceedings of the Indian National Science Academy, 87(2), 191-198. https://doi.org/10.1007/s43538-021-00027-4

UGC Care & Scopus Listed Journal :
Proceedings of the Indian National Science Academy (Springer)
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[2] Naik, A., & Thaker, H. T. (2022). EARLY RECOGNITION OF MUNG LEAF DISEASES BASED ON SUPPORT VECTOR MACHINE AND CONVOLUTIONAL NEURAL NETWORK. INFOCOMP Journal of Computer Science, 21(1).

https://infocomp.dcc.ufla.br/index.php/infocomp/article/view/1840

UGC Care Listed Journal :
INFOCOMP Journal of Computer Science
E-ISSN : 1982-3363

[3] Naik, A., Thaker, H., & Desai, N. (2022). Creation and Segmentation of Image Dataset of Mung Bean Plant Leaf. In *Micro-Electronics and Telecommunication Engineering* (pp. 669-683). Springer, Singapore. https://link.springer.com/chapter/10.1007/978-981-16-8721-1_63

Scopus Listed journal:

Micro-Electronics and Telecommunication Engineering Part of the Lecture Notes in Networks and Systems book series (LNNS,volume 373)

Appendix – B (International Conferences)

[1] Naik, A., Thaker, H., & Desai, N. (2022). Creation and Segmentation of Image Dataset of Mung Bean Plant Leaf. In International research conference on IoT,Cloud and Data Science (IRCICD'21),SRM institute of science and technology Chennai .

[2] Naik, A., Thaker,H. Early recognition of mung leaf diseases based on support vector machine and convolutional neural networks in uncontrolled environment. In International conference on emerging trends & contemporary practices 2022, Atmiya University, Rajkot.

Appendix – A (1)

A SURVEY ON VARIOUS IMAGE PROCESSING TECHNIQUES AND MACHINE LEARNING MODELS TO DETECT, QUANTIFY AND CLASSIFY FOLIAR PLANT DISEASE

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ABSTRACT

Agriculture is one of the significant factors that drive India's economy. A decrease in the yield of agricultural food crops due to plant diseases results in great loss to the economy of the developing country. Detection of plant disease at an early stage will decrease the chance of loss on the overall economy. Nowadays, ICT (Information And Communication Technology) plays a major role in all sectors including agriculture. Classical agriculture has been reformed using ICT. Farmers are getting the correct information on time. ICT is necessary for agriculture, it may increase productivity using data generation, storage, and analysis. This paper presents a survey of various image processing techniques and machine learning tools to detect, quantify, and classify plant diseases. Methods that explore visible symptoms in leaves and stems were considered. This paper aims on exploring this wide research area and possible scope of further researcher there by looking at various aspects of review such as accuracy, image processing techniques, machine learning models, and plants on which work has been carried out. This survey is likely to be useful to researchers working both on disease detection on the leaf and pattern recognition, providing a quick overview of this important field of research.

Keywords: Image Processing, Plant Disease, K-Means, Neural Network, SVM.

1. INTRODUCTION

Food security is a major concern in modern society. Plant disease is greatly affecting the yield of agricultural crops and it is an immense threat to food security. Early identification of plant disease can decrease the effect of disease on crop yield. Agriculture has become much more than simply a means to feed ever-growing populations. Plants have become an important source of energy, and are a fundamental piece in the puzzle to solve the problem of global warming (Barbedo, 2013). Several diseases distress plants with the latent to cause devastating economical, social, and ecological losses. Therefore, detecting diseases in an accurate and timely way is the most important task. In tropical countries like India, yields of agricultural crops are immensely affected by various plant diseases. Early identification of these diseases can be useful to abolish the effect of disease on crop yield. Empirical techniques of identification are time consuming and lengthy. It is noteworthy that most plant diseases produce different symptoms on the surface of the leaves. Most diseases, however, generate some kind of manifestation in the visible spectrum. In the vast majority of the cases, the diagnosis, or at least a first guess about the disease, is performed visually by humans. Farmers can take and upload an image using smartphones. Trained raters may be efficient in recognizing and quantifying diseases, however, they have associated some disadvantages that may harm the efforts in many cases (Barbedo, 2013). (Bock CH, 2010) et al. list some of those disadvantages. However, these symptoms can be identified using various digital image analysis techniques. Image analysis techniques can be useful to resolve this problem. A relationship between digital numbers in various pixels can be identified from the image. Pixel-wise classification techniques can be applied to identify disease symptoms on the leaves of the plant.

2. LITERATURE REVIEW

Methods are exploring visual cues present in almost all of those parts, like roots (Smith SE, 1991), kernels (Ahmad IS, 1999), fruits (Aleixos N, 2002) (Corkidi G, 2005) (López-García F, 2010), stems and leaves. However, the present work concentrates, particularly on plant leaves.

Pujari (2013) et al. have projected statistical tool for sensing and classifying fungal disease. The classification is constructed on infection severity. Images of fruits affected by diverse fungal infection signs are collected and characterized based on infection severity as partly affected, soberly affected, harshly affected, and standard. (M. Malathi, 2015) et al. provided a review of plant foliage disease recognition using image processing methods. With the help of programmed image processing methods that can sense diseased foliage using pigment data of leaves. The technique projected by Sena DG Jr (2003) et al. aims to distinguish amongst maize plants affected by fall armyworm from healthy ones using digital images. They separated their procedure into two main stages: image processing and image analysis. In the image processing stage, the image is altered to a greyscale, threshold, and sieved to eliminate false objects. In the image analysis stage, the entire image is separated into 12 blocks. Slabs whose foliage area is fewer than 5% of the total area are discarded. For each residual block, the number of linked objects, representing the unhealthy regions, is counted. The plant is considered infected if this number is above a threshold, which, after empirical evaluation, was set to ten. The method proposed by Tucker CC (1997) et al. objects to enumerate and recognize infections in sunflower and oat foliage. The first step of the system is a separation whose threshold differs rendering to the disease being considered. The subsequent pixels are associated with gatherings, representing the unhealthy regions. Martin DP (1998) et al. suggested a technique to enumerate the indications caused by the maize streak virus. The scheme projected by Skaloudova B (2006) et al. measures the mutilation produced in the foliage by spider mites. The final assessment is given by the ratio amongst the quantities of pixels in affected regions divided by the total amount of pixels of the leaf. However, most of the fruitful study is focused on three Methods K – Mean, Neural Networks, and Support Vector Machines. Therefore, in the present study, we tried to review these three methods in detail.

3. K – Mean

K-Means unsupervised classification calculates initial class means evenly distributed in the data space then iteratively clusters the pixels into the nearest class using a minimum distance technique. Each iteration recalculates class means and reclassifies pixels concerning the new means. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified, in which case some pixels may be unclassified if they do not meet the selected criteria. This process continues until the number of pixels in each class changes by less than the selected pixel change threshold or the maximum number of iterations is reached.

3.1 K-Means Clustering

There are multiple ways to cluster the data but the K-Means algorithm is the most used algorithm. Which tries to improve the intergroup similarity while keeping the groups as far as possible from each other.
Basically, K-Means runs on distance calculations, which again uses "Euclidean Distance" for this purpose. Euclidean distance calculates the distance between two given points using the following formula:

$$\text{Euclidean Distance} = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2}$$

The above formula captures the distance in 2-Dimensional space but the same is applicable in multi-dimensional space as well with the increase in the number of terms getting added. "K" in K-Means represents the number of clusters in which we want our data to divide. The basic restriction for the K-Means algorithm is that your data should be continuous in nature. It won't work if data is categorical in nature (ENVI, 2009) (Unscrambler Users Guide, 1997).

3.2. Review of K-Means method

H. Al-Hiary (2011) et al. developed a software solution for instinctive recognition and classification of plant leaf diseases. The dispensation scheme contains four main stages. The applications of K-means clustering and Neural Networks (NNs) were articulated for the classification of diseases on plant leaves. Al Bashish D (2010) et al. suggested an image-processing-based attitude, used for leaf and stem disease recognition using K – Mean classification. Wang et al., (2012) concluded that K – Mean classification is better for image recognition of two kinds of wheat and grape diseases. Narmadha and Arulvadivu (2017) Sensed Paddy Leaf Disease Indications by means of Image Processing and K-means techniques. Suresha et al., (2017) attained an accuracy of 77 % for the detection of Diseases in Paddy Leaves with the help of a kNN Classifier. Dr. Sridhathan et al. (2018) established an algorithm for recognition of disease using image processing. For color separation K – Mean is suitable while GLCM classification achieved 98.27% accuracy.

One can infer concerning K-Mean from the above literature review that this classification method performs well with less complex classes. The application of K-mean to separate less complex variables, features, or classes always worked well. It is noteworthy that the K-means method is active in constructing decent clustering results for many applied applications.

However, k-means has trouble clustering data where clusters are of fluctuating sizes and compactness. Moreover, the K-mean classification mechanism yielded comparatively less accuracy (<80 %).

4. Neural networks

Use Neural Net to apply a layered feed-forward neural network classification technique. The Neural Net technique uses standard backpropagation for supervised learning. You can select the number of hidden layers to use and you can choose between a logistic or hyperbolic activation function. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. The error is back-propagated through the network and weight adjustment is made using a recursive method. You can use the Neural Net classification to perform non-linear classification (Figure 1) (ENVI, 2009) (Unscrambler Users Guide, 1997).

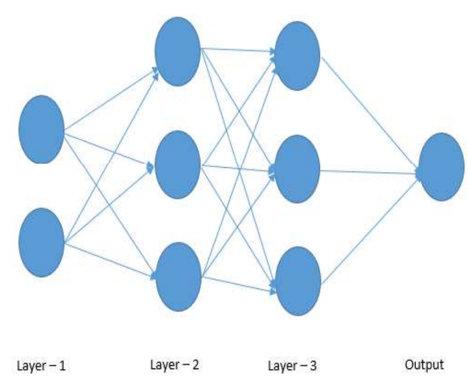

Figure 1: Graphic representation of Neural Network method

4.1 Review of Neural networks method

An initial effort to monitor plant health was supported by Hetzroni et al. (1994). Their scheme tried to recognize iron, zinc, and nitrogen deficits by monitoring lettuce leaves. Those strictures are finally nourished to neural networks and statistical classifiers, which are used to recognize the plant condition. Pydipati et al. (2005) likened two dissimilar methods to sense and classify three types of citrus ailments. The primary method was based on a Mahalanobis minimum distance classifier, using the nearest neighbor value. The second tactic castoff radial basis functions (RBF) neural network classifiers skilled with the backpropagation algorithm. Conferring to the authors, both the classification methods performed alike, by means of the finest of the four subsets, which contained ten hue and saturation texture features. Huang (2007) projected a system to sense and classify three kinds of diseases that affect Phalaenopsis orchid seedlings. Earlier, Linderman (2004) et al. have reported that the neural network is probably more proficient for the classification of minor and complex features.

The ANN classifier was able to classify correctly even those quadrats which are having a lesser percentage of occupancy (Vyas, 2011) et al. Kulkarni and Patil (2012) projected a methodology for detecting plant diseases, using image processing procedures and Artificial Neural Network (ANN). An ANN-based classifier is approved which uses the mixture of color and texture features to distinguish and classify diverse plant diseases. The scheme projected by Abdullah et al. (2007) attempted to discriminate a plant disease of rubber tree leaves, Principal Component

Analysis (PCA) is applied straight to the RGB values of a low-resolution image of the leaves. The first two principal components are then nourished to a Multilayer Perceptron (MLP) Neural Network with one hidden layer, whose output reveals if the sample is diseased or not. Singh and Misra, (2017) developed an algorithm for image division method Which is used for automatic detection and classification of plant leaf diseases with the help of Artificial Neural Network, Bayes classifier, Fuzzy Logic, and hybrid algorithms. Hidayatuloh et al. (2018) effectively detected tomato plant disease through its leaf image automatically with an accuracy of identification of 86.92% using Neural Network (CNN).

We can infer that Neural Network works well for complex clustering of variables or classes. Very high accuracy was obtained (>80%) for the classification of various classes with the help of Neural Network. NN worked fared better with the higher complexity of the data set.

5. Support vector machines (SVM)

SVM is a classification method based on statistical learning wherein a function that describes a hyperplane for optimal separation of classes is determined. As the linear function is not always able to model such a separation, data are mapped into a new feature space and a dual representation is used with the data objects represented by their dot product. A kernel function is used to map from the original space to the feature space and can be of many forms, thus providing the ability to handle nonlinear classification cases. The kernels can be viewed as a mapping of nonlinear data to a higher dimensional feature space while providing a computation shortcut by allowing linear algorithms to work with higher dimensional feature space. The support vector is defined as the reduced training data from the kernel. The figure below illustrates the principle of applying a kernel function to achieve separability (Figure 2).

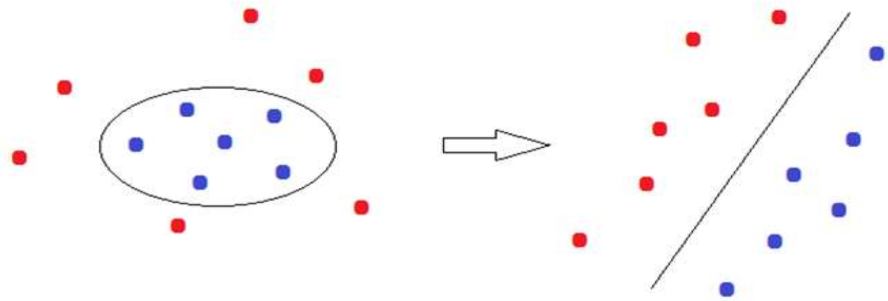

Figure 2: Graphic representation of the SVM method (CAMO unscramble ®)

In this new space, SVM will search for the samples that lie on the marginal amongst the classes, i.e. to find the samples that are ideal for unraveling the classes; these samples are named support vectors. The figure below exemplifies this in that only the samples marked with positive for the two classes are used to produce the rule for classifying new samples (ENVI, 2009) (Unscrambler Users Guide, 1997).

5.1 Review of SVM

Meunkaewjinda et al. (2008) proposed a technique to identify and classify diseases that affect grape-vines. The colors present on the leaves are then clustered by means of an unsupervised and untrained self-organizing map, diseased and healthy regions are then separated by a Support Vector Machine (SVM). Youwen et al. (2008) proposed a technique to recognize two diseases that can appear in cucumber leaves, some color, shape, and texture features are extracted. Those features feed an SVM, which performs the final classification. The authors stated that the results provided by the SVM are far better than those achieved using neural networks. The system proposed by Yao et al. (Yao Q, 2009) aimed to identify and classify three types of diseases that affect rice crops. Color, shape, and texture features are extracted, the latter one from the HSV color space. Finally, the features are submitted to a Support Vector Machine, which performs the final classification. Jian and Wei (2010) proposed a technique to identify three types of cucumber leaf diseases. As in most approaches, the separation between healthy and diseased regions is made by a simple thresholding procedure (Barbedo, 2013). In the following, a variety of color, shape, and texture features are extracted. Those features are submitted to an SVM with Radial Basis Function (RBF) as the kernel, which performs the final classification. Jagadeesh D. Pujari et al. (2013) proposed a technique for quantitative detection and classifying disease on Mango, Pomegranate, and Grape and achieved 76.6% accuracy (ENVI 4.7 User guide ®).

The Support Vector Machine (SVM) is an effective distribution-free classifier that has been extensively used in the current decade for solving various image classification problems. We can infer that SVM achieved moderate accuracy in classifying complex clusters of pixels.

6. Detection

Detection helps to identify whether the plant leaves is affected by some disease or not. There are many image processing techniques and machine learning tools to detect plant leave disease. In the following table, a detailed survey of various research papers is given based on Detection.

Table1: Detailed Survey Of Research Papers based on Detection

AUTHOR	CORE ANALYSIS TOOL	PLANT	ACCURACY
(Sena DG Jr, 2003) et al.	Thresholding	Maize	94.72%
(Pydipati R, 2005) et al.	NN	Citrus Plant	95%
(Abdullah NE, 2007) et al.	Neural networks	Rubber tree	70%
(Story D, 2010) et al.	Dual-segmented regression analysis	Lettuce	N/A
(Wang H, 2012) et al.	K-MEAN	Wheat Plant	97.14%
(R.P.Narmadha, 2017) et al.	K-MEAN	Paddy Plant	N/A
(Akbar Hidayatuloh, 2018) et al.	CNN	Tomato	86.92%

7. Quantification

Quantification helps to quantify the symptoms and measures the damage caused in leaves to identify whether the plant leaves are affected by some disease or not. In the following table, a detailed survey of various research papers is given based on Quantification.

Table 2: Detailed Survey Of Research Papers based on Quantification

AUTHOR	CORE ANALYSIS TOOL	PLANT	ACCURACY
(Lindow SE, 1983) et al.	Thresholding	Sycamore, fern, tomato, buckeye	Better accuracy and precision
(Price TV, 1993) et al.	Thresholding	Coffee	
(Olmstead JW, 2001) et al.	3rd party package	Cherry	N/A
(Skaloudova B, 2006) et al.	Thresholding	Bean	N/A
(Camargo A, 2009) et al.	Thresholding	Banana, maize, soy, alfalfa, cotton	69.0%
(Pagola M, 2009) et al.	Color analysis	Barley	N/A
(Macedo-Cruz A, 2011) et al.	Thresholding	Oat	92%
(Martin DP, 1998) et al.	Thresholding	Maize	96.4%
(Pang J, 2011) et al.	Region growing	Maize	92%
(Patil SB, 2011) et al.	Thresholding	Sugar cane	98.60%
(Lloret J, 2011) et al.	Thresholding	Grapes	N/A
(Peressotti E, 2011) et al.	3rd party package	Grapes	N/A
(Sannakki SS, 2011) et al.	Fuzzy logic	Pomegranate	Accurate & Satisfactory
(Coninck BMA, 2012) et al.	3rd party package	Sugar beet	N/A
(Contreras-Medina LM, 2012) et al.	Color analysis	Pumpkin, pepper, bean	N/A

(Jagadeesh D. Pujari, 2013) et al.	Thresholding	Mango, Pomegranate, Grape	94.085%

8. Classification

Classification helps to categorize the data into various classes like disease or severity wise. The detailed survey of research papers based on classification is given in the following table.

Table3: Detailed Survey Of Research Papers based on Classification

AUTHOR	CORE ANALYSIS TOOL	PLANT	ACCURACY
(Pydipati R, 2005) et al.	Neural networks	Citrus	95%
(Pydipati, 2006) et al.	Self-organizing maps	Orange	96%
(KY, 2007) et al.	Neural networks	Orchid	89.6%
(Camargo, 2009) et al.	SVM	Cotton	90%
(Anthonys G, 2009) et al.	Membership function		70%
(Kawcher Ahmed, 2019) et al.	KNN		97%
(Kurniawati NN, 2009) et al.	Feature-based rules		94.7%
(Kurniawati NN, 2009) et al.	Feature-based rules		87.5%
(Rakesh Kaundal, 2006) et al.	SVM	Rice	97.2%
(Al Bashish D, 2010) et al.	Neural networks	N/A	93%
(Kai S, 2011) et al.	Neural networks		98%
(V. N. T. Le, 2019) et al.	SVM	Maize	91.85%
(Suresha M, 2017) et al.	KNN		76.59%
(Kholis Majid, 2013) et al.	Fuzzy Logic and PNN	Padddy Plant	91.46%
(Dr. Sridhathan C, 2018) et al.	K-Mean	N/A	98.27%
(G. Dhingra, Mar-2019) et al.	SVM	Basil	98%
(G. Saleem, Feb - 2019) et al.	KNN	N/A	96%
(Y. Sun, 2019) et al.	SVM	Tea Plant	98.5%
(Sanjeev S Sannakki, 2013) et al.	NN	Grape	100% for Downy affected region and Powdery affected region
(S.Sivasakthi, 2020)	SVM & ANN	Greenhouse Crop	92% (SVM) 87% (ANN)

9. Comparative Analysis of Various Methodologies

The following table compares various methods represented in the reviewed papers. The comparison shows that SVM performs better than other methods and provide better accuracy.

AUTHOR	CORE ANALYSIS TOOL	Task	ACCURACY
Plant : Rice / Paddy Plants			
(Kholis Majid, 2013) et al.	Fuzzy Logic and PNN		91.46%
(Suresha M, 2017) et al.	KNN		76.59%
(Rakesh Kaundal, 2006) et al.	SVM		97.2%
(Kawcher Ahmed, 2019) et al.	KNN		97%
(Kurniawati NN, 2009)	Feature-based rules		94.7%
(Kurniawati NN, 2009)	Feature-based rules	Classification	87.5%
Greenhouse Crops			
(S.Sivasakthi, 2020)	SVM & ANN	Classification	92% (SVM)

			87% (ANN)
Maize			
(Martin DP, 1998)	Thresholding	Quantification	96.4%
(Pang J, 2011)	Region growing	Quantification	92%

10. CONCLUSION:

The extensive diversity of applications on the subject of identifying objects in digital images makes it hard for someone to outlook all possible treasured ideas present in the literature. In this context, this paper tried to present a short review on the subject, pointing at being a starting point for those researching the issue. The present survey paper gives a squat survey on leaf disease detection and classification techniques using image processing. There are many methods in automated or computer vision for disease detection and classification but still, there is a lack of this research topic. All diseases cannot be identified using a single method. From the study of the above classification techniques, we come up with the following conclusion.

The present study concludes, that the K-Mean classification method performs well with less complex classes. However, the K-mean classification mechanism yielded comparatively less accuracy (<80 %). Moreover, Neural Network works well for complex clustering of variables or classes. Very high accuracy was obtained (>80%) for the classification of various classes with the help of Neural Network. NN worked fared better with the higher complexity of the data set. It is noteworthy that The Support Vector Machine (SVM) is an operative distribution-free classifier that has been widely used and SVM achieved moderate accuracy in classifying composite clusters of pixels.

Different authors used different algorithms for accurate detection of diseases. The advantage of using the image processing method is that the leaf diseases can be identified at its early stage. For improving the recognition rate, most researchers used artificial neural networks and classifiers like Bayes classifier, Fuzzy Logic, K-means clustering, etc.

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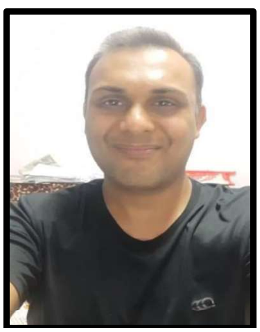

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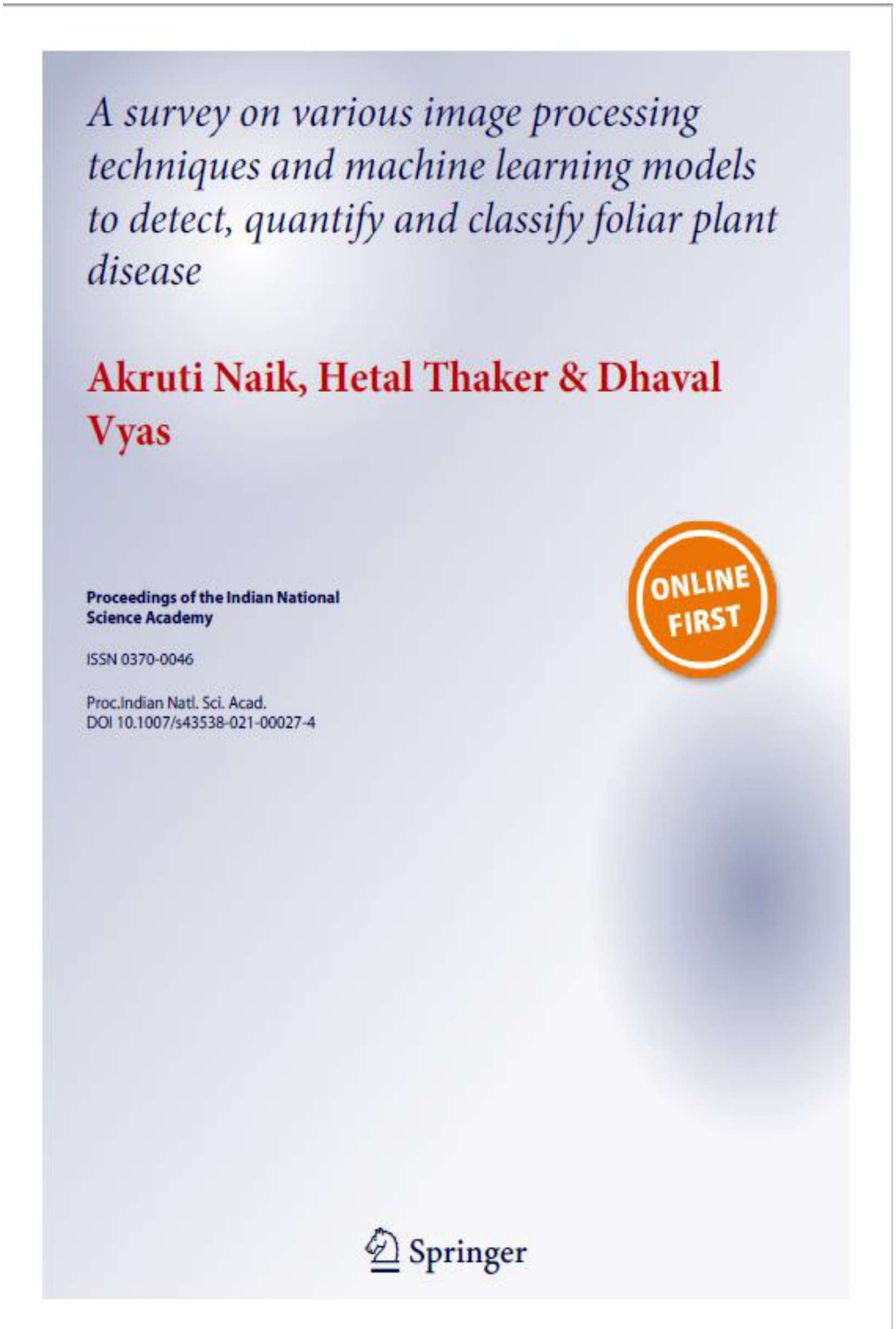

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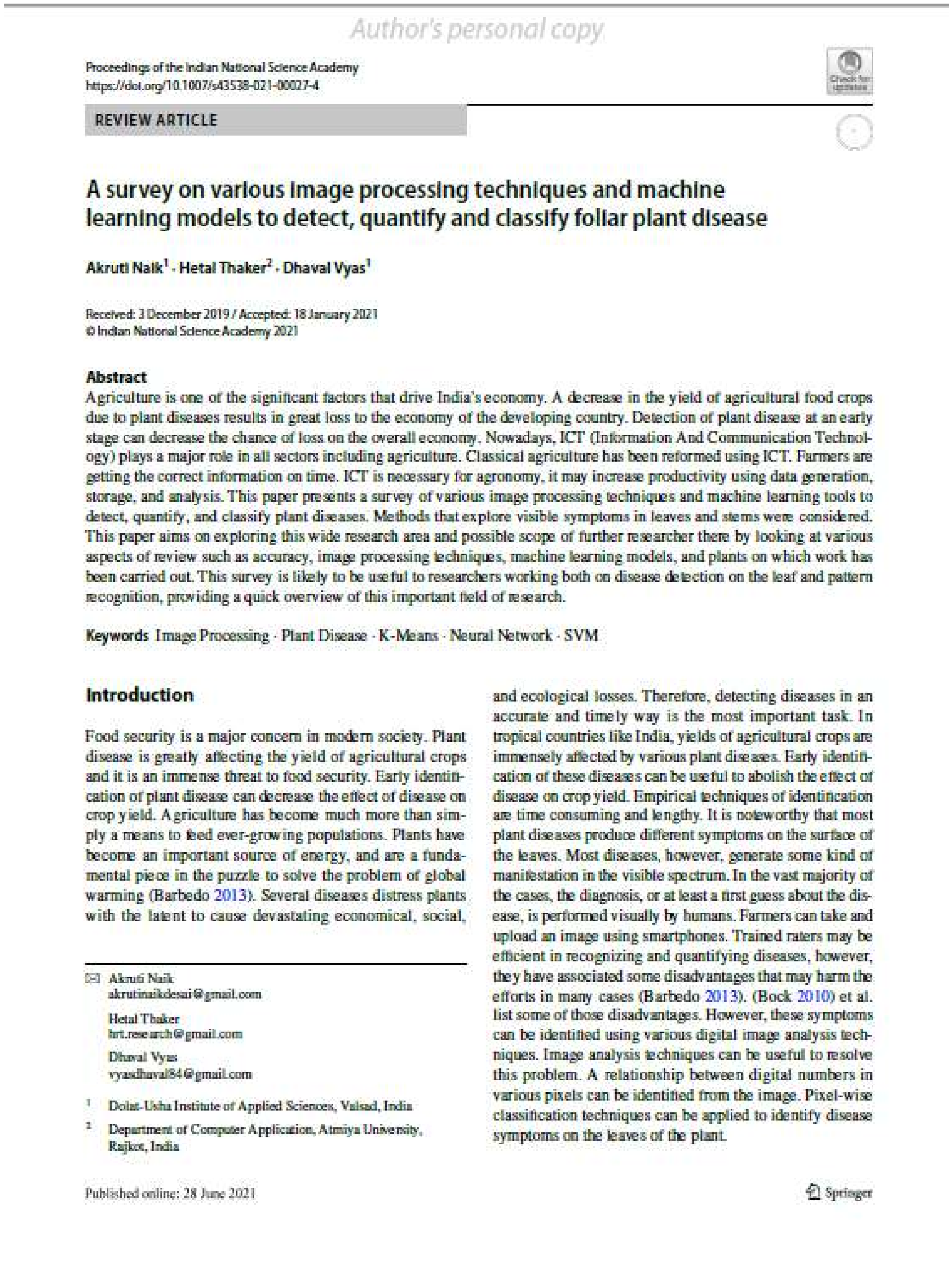

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REVIEW ARTICLE

A survey on various image processing techniques and machine learning models to detect, quantify and classify foliar plant disease

Akruti Naik[1] · Hetal Thaker[2] · Dhaval Vyas[1]

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Abstract
Agriculture is one of the significant factors that drive India's economy. A decrease in the yield of agricultural food crops due to plant diseases results in great loss to the economy of the developing country. Detection of plant disease at an early stage can decrease the chance of loss on the overall economy. Nowadays, ICT (Information And Communication Technology) plays a major role in all sectors including agriculture. Classical agriculture has been reformed using ICT. Farmers are getting the correct information on time. ICT is necessary for agronomy, it may increase productivity using data generation, storage, and analysis. This paper presents a survey of various image processing techniques and machine learning tools to detect, quantify, and classify plant diseases. Methods that explore visible symptoms in leaves and stems were considered. This paper aims on exploring this wide research area and possible scope of further researcher there by looking at various aspects of review such as accuracy, image processing techniques, machine learning models, and plants on which work has been carried out. This survey is likely to be useful to researchers working both on disease detection on the leaf and pattern recognition, providing a quick overview of this important field of research.

Keywords Image Processing · Plant Disease · K-Means · Neural Network · SVM

Introduction

Food security is a major concern in modern society. Plant disease is greatly affecting the yield of agricultural crops and it is an immense threat to food security. Early identification of plant disease can decrease the effect of disease on crop yield. Agriculture has become much more than simply a means to feed ever-growing populations. Plants have become an important source of energy, and are a fundamental piece in the puzzle to solve the problem of global warming (Barbedo 2013). Several diseases distress plants with the latent to cause devastating economical, social, and ecological losses. Therefore, detecting diseases in an accurate and timely way is the most important task. In tropical countries like India, yields of agricultural crops are immensely affected by various plant diseases. Early identification of these diseases can be useful to abolish the effect of disease on crop yield. Empirical techniques of identification are time consuming and lengthy. It is noteworthy that most plant diseases produce different symptoms on the surface of the leaves. Most diseases, however, generate some kind of manifestation in the visible spectrum. In the vast majority of the cases, the diagnosis, or at least a first guess about the disease, is performed visually by humans. Farmers can take and upload an image using smartphones. Trained raters may be efficient in recognizing and quantifying diseases, however, they have associated some disadvantages that may harm the efforts in many cases (Barbedo 2013). (Bock 2010) et al. list some of those disadvantages. However, these symptoms can be identified using various digital image analysis techniques. Image analysis techniques can be useful to resolve this problem. A relationship between digital numbers in various pixels can be identified from the image. Pixel-wise classification techniques can be applied to identify disease symptoms on the leaves of the plant.

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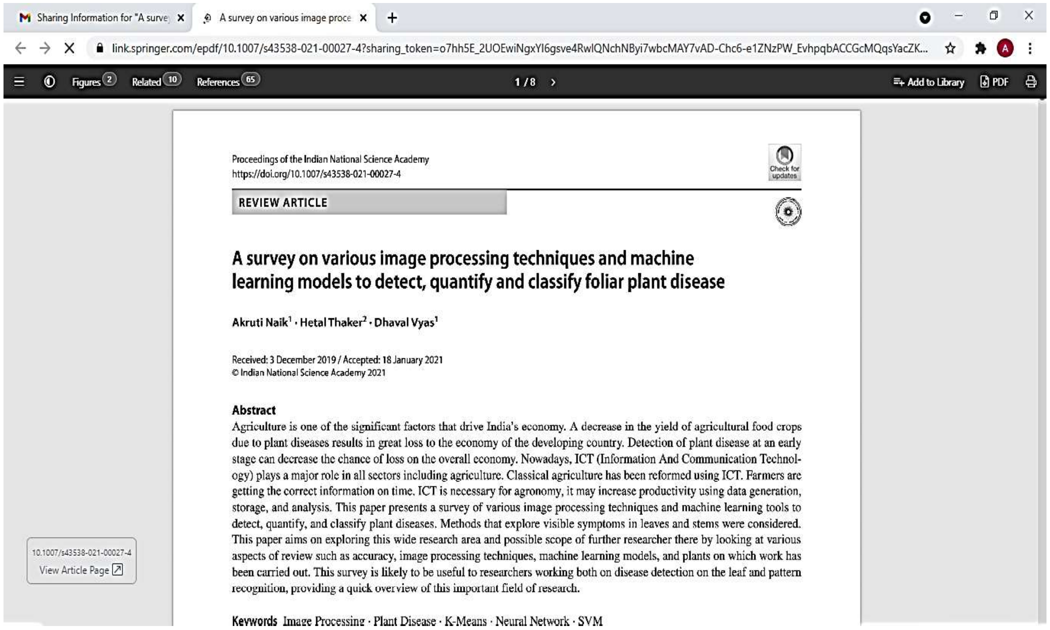

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REVIEW ARTICLE

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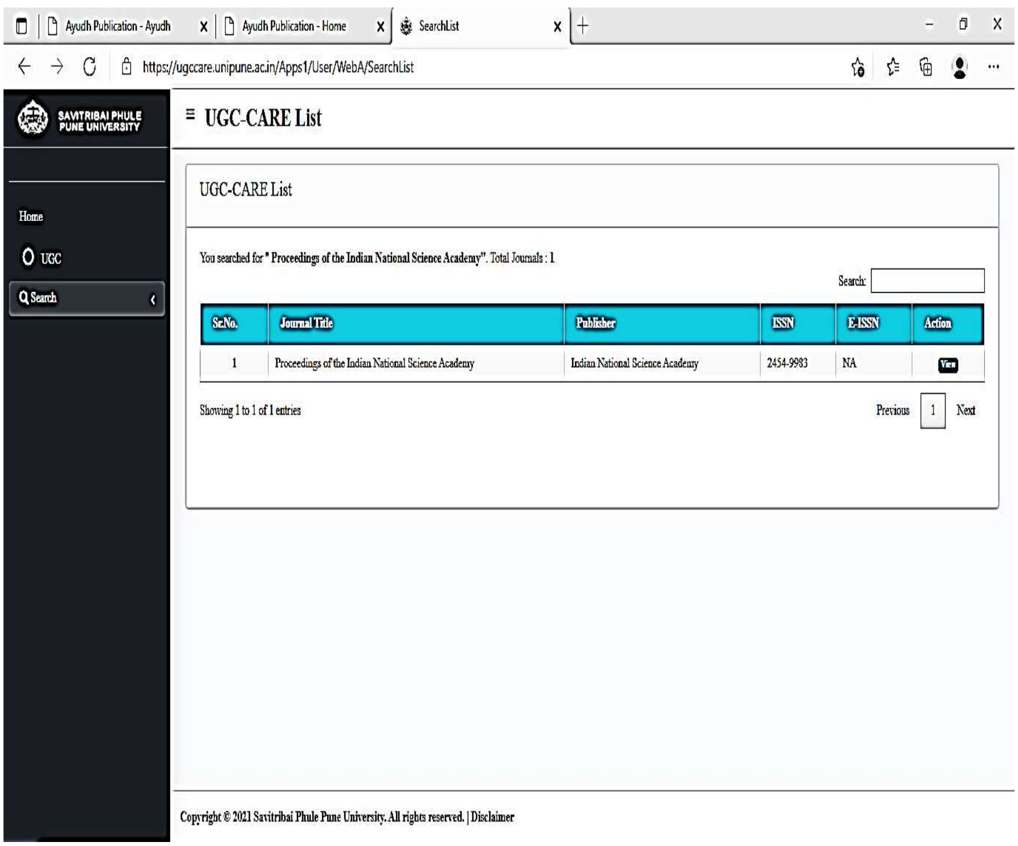

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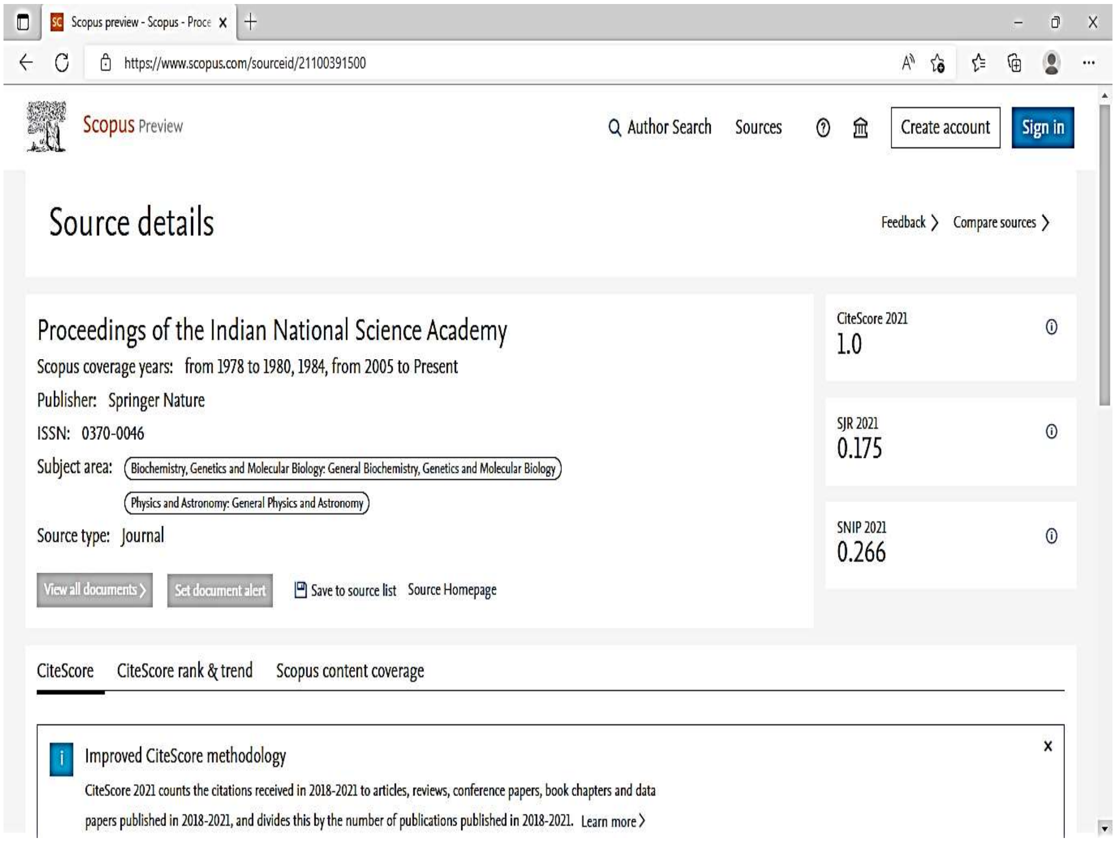

Figure: Scopus Coverage

Appendix – A (2)

EARLY RECOGNITION OF MUNG LEAF DISEASES BASED ON SUPPORT VECTOR MACHINE AND CONVOLUTIONAL NEURAL NETWORK

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Abstract— This paper proposed a model that Classifies a Mung (*Vigna mungo L.*) leaf to check if it is healthy or infected with a disease with the aid of Machine Learning and Deep Learning algorithms. The dataset is created in a controlled environment, where a controlled environment is a data item (image) that comprises only a single subject (leaf) and a white background collected from the south Gujarat Region in India. SVM and CNNs with different architectures have been trained and compared to each other. It aimed at detecting 3 mung leaf disease categories and a healthy leaf category. The model extracts complex features of various diseases. Comparative experiment results show that in the proposed work SVM overfit the data and CNN achieves 95.05% identification accuracy on the Mung leaf image dataset. Early detection will help farmers to improve their productivity. The main objective was to automate Mung Leaf disease identification using advanced deep learning approaches and image data.

Keywords— Mung leaf, Classification in Machine Learning, SVM, Deep Neural Networks, Convolutional Neural Networks

1. Introduction

Mungbean is also known as green gram which is a highly nutritious legume crop and considered as a quality pulse due to its rich protein content and excellent digestibility. India is the largest producer of mungbean where it is the third most important pulse crop with an area of approximately 34.50 lakh hectares with 15.91 lakh tonnes of total production [1]. To meet global demand, it is commanding to increase the current average global productivity [2]. Having diseases in plants is a natural process. In traditional practice, farmers try to evaluate the diseases by their past experience. Or in other cases, the expert observes the plant organs like leaves and stems for any diseases. It is a very time-consuming and costly method because it requires continuous monitoring by an expert in large fields. Early identification and treatment will help farmers to reduce the overall loss. We require a fast approach to protect the crop from diseases. Using advanced technology like mobile phones, tablets, and similar devices farmers can input data in form of digital images and get an immediate response. That will result in crop productivity. We need automated approaches that can support farmers in the early detection and prevention of Mung leaf diseases. Machine Learning and Deep Learning are part of Artificial Intelligence that emphasizes making predictions using algorithms that increase automatically through experience and by the use of data. Algorithms build an inference model based on training data to generalize the context and make predictions. Different deep learning models such as VGG16, MobileNetV2, and Custom CNN were implemented. Here we try to classify a mung leaf to check if it is healthy or diseased. Our model performance showed favourable results.

2. Related Work

The yield of mungbean is affected by several diseases from which the three most common mung leaf diseases are Cercospora Leaf Spot, Powdery Mildew, and Yellow Mosaic Virus.

Mungbean yellow mosaic disease (MYMD) is one of the major destructive diseases of mungbean in India. It was first reported on Mungbean from India in 1940 [3], since then, it has been reported from all over India and other countries of the Indian subcontinent [4]. When it is severe crop losses extent up to 85-90%. It's considered to be a potential threat to the cultivation of not only mungbean but also in other species like soybean, urdbean, moth bean, and cowpea [5].

CLS is the most widespread and destructive fungal disease of the mungbean. Cercospora leaf spot disease caused by Cercospora spp. The disease was first time reported in Delhi, India [6]. Cercospora leaf spot is also causing serious losses to mungbean crop. It 58% yield loss annually [7]. The disease starts appearing about 30-40 days after planting. The leaf spots develop on infected leaves with a somewhat circular/subcircular to broadly irregular shape, the central area turn reddish-brown and grey center surrounded by a dark brown margin.

Powdery mildew diseases in mungbean caused by the fungal pathogen Erysiphe polygoni. Yield losses due to the disease were reported to be up to 20-40% at the reproductive stages [8], but the damage can be more serious when the epidemic starts at the reproductive stages it may reach up to 55% [9].

Each disease has unique symptoms that appear on the leaf, which can be used to categorize the disease by deep learning algorithms [10] [11] [12] [13].

Deep learning for plant disease detection in the primary works [14] [15] [16] [17] all used leaf images as a data source. However, these methods require a lot of data to work accurately, and this might be a challenge. Initially, gathering new data for the problem domain, for example, object identification in biomedical or medical images may be difficult [18] [19] [20]. Besides, once the images have been gathered, they must be manually labelled and this is a laborious task and involves an expert's view to conducting it properly [21].

Data augmentation is an effective method that deals with a limited amount of data [22] [23]. This method generates new training samples from the original dataset by applying transformations to them. Several libraries like Tensorflow [24], Augmentor [25], or Imgaug [26], provide features for augmentation. However, these libraries not meant to be deal with object localization, object detection, semantic segmentation, and instance segmentation. Transformation methods used to perform augmentation on images may alter the notation but do not change the class of the image. For illustration, the horizontal or vertical flip operation to an image does not change the class of image, but only the location of the objects in the new image has changed. So for each problem, a special-purpose technique needs to be implemented, or augmented images must be manually labelled. Both the solutions are not feasible when there are hundreds or thousands of images to deal with.

For training using Convolutional neural networks (CNNs) require a large number of sample images. Collecting required images is time-consuming and costly in many applications [27]. For limited dataset conditions, many researchers combined deep learning with transfer learning for data expansion [28]. A method of deep learning model combined with transfer learning proposed by Srdjan [29] classifies 13 different diseases and healthy plant leaf and reaches 96.3% average accuracy. Liu et al.[30] increases the size of the training dataset 12 times by applying rotation, mirroring, brightness, and contrast adjustment and adding Gaussian noise, and reducing the overfitting problem.

Mohanty et al.[31] classify and recognize 54,306 diseased and healthy plant leaf images using GoogleNet and AlexNet and conclude that GoogleNet provides a better average classification effect than AlexNet and achieves accuracy on the test set up to 99.35%. Wang et al. [32] trained a chain of deep convolutional neural networks that detect the severity of diseases and found that VGG16 is the best model and achieves 90.4% of accuracy.Too et al., [33] performs comparative test and verified that compared to VGG and ResNet, DenseNets requires fewer parameters and less calculation time to achieve advanced performance and achieve 99.75% test accuracy. Three different CNN architectures were retrained by [34] using the transfer learning method and deep transfer learning was performed using pre-trained models that generate networks that could make accurate predictions. Three methods of regression, focus loss function, and multilabel classification based on DenseNet-121 CNN was proposed by [35] to identify apple leaf diseases and achieve 93.51, 93.31, and 93.71% accuracy on the test set.

3. Proposed Method

The proposed algorithms for this work we have used Support Vector Machine and Convolutional Neural Networks to detect mung leaf disease through machine-learning and deep learning.

Support Vector Machines (SVMs) is a model that can be used for both classification and regression. The algorithm tries to find a decision boundary, or a hyperplane when data is characterized in more than two dimensions that splits the classes.

A Convolutional Neural Network is a type of neural network that can successfully recognize the Spatial and Temporal dependencies in the data by passing through multiple filters. It is frequently used with images. The architecture of the Convolutional Neural Network is designed in such a way that it performs better because of the relatively different number of parameters involved and the reusability of weights. The pre-processing steps required for ConvNets are considerably less compared to traditional machine learning algorithms. Each image when training goes through a series of operations, known as convolutions, a dot product of a 2D kernel of a specified size is slid over the image and the small region of the image the kernel is connected to. The resultant is then followed by an activation function like ReLU (Rectified Linear Unit) and then followed by a Pooling layer that generally reduces the image resolution by making it half the number of pixels. After this, stacked layers of the fully connected layer are usually added to learn non-linear combinations of the high-level features presented by the convolutional layers. But before passing the feature maps to the fully connected layers, there is a need to flatten the features maps. Figure 1 shows the structure of the Mung Leaf disease detection system.

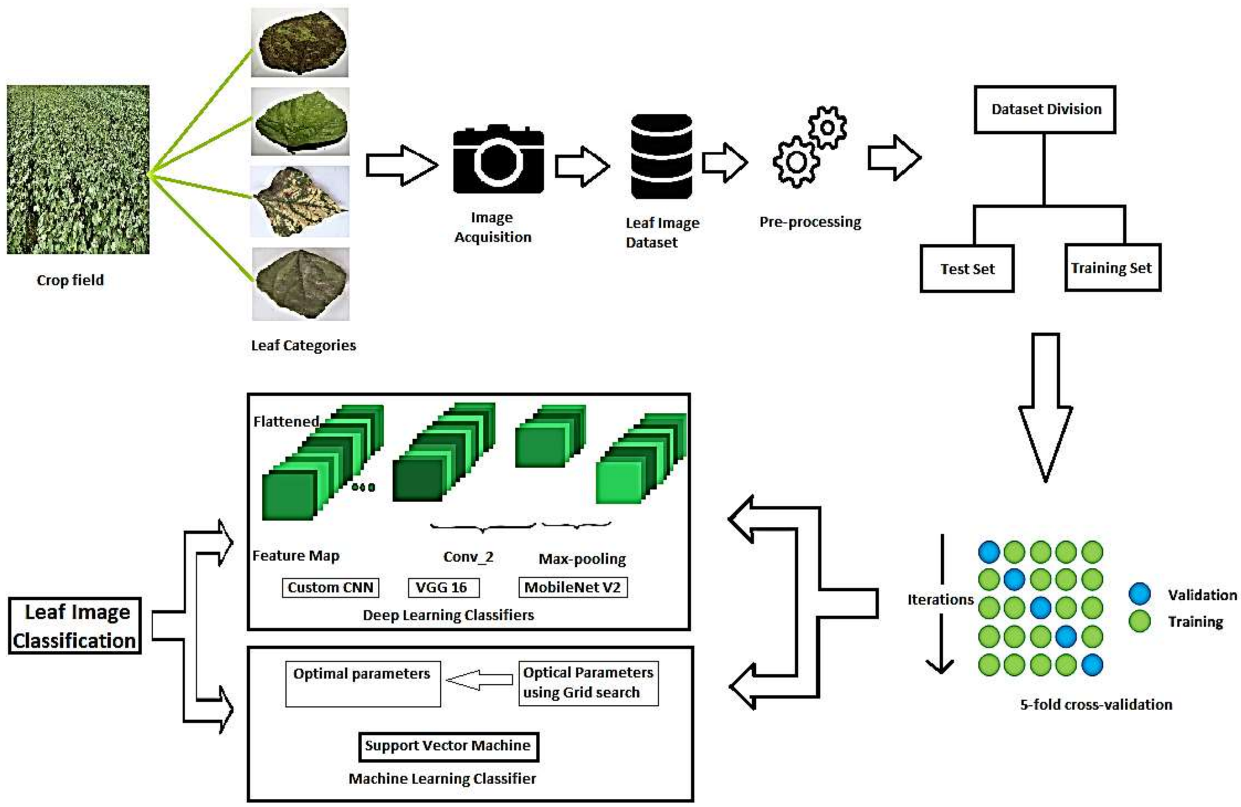


Figure 12: The Structure of Mung Leaf Disease Detection

4. DATASET AND PREPROCESSING

4.1 The Dataset

The dataset primarily accounts for a controlled environment. An image from the controlled environment contains a single mung leaf with a white background i.e. no noise. After image acquisition, the images are manually screened to avoid duplication and classification in the dataset. Finally, a dataset contained a total of 883 Mung leaf images for controlled environments: Cercospora (224), Healthy (211), Powdery Mildew (225), and Yellow Mosaic (223) is obtained. After that size of each picture is fixed at 256 x 256. A leaf can be one of the four distinct categories i.e. Healthy, Cercospora, Yellow Mosaic, and Powdery Mildew.

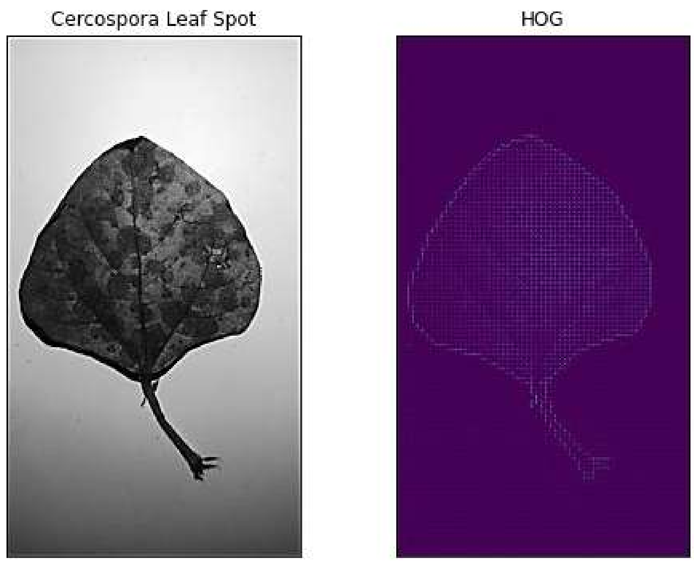
The images of Mung leaves in 4 categories are shown in Figure 2.

(a) Yellow Mosaic Virus (b) Cercospora Leaf Spot (c) Powdery Mildew (d) Healthy

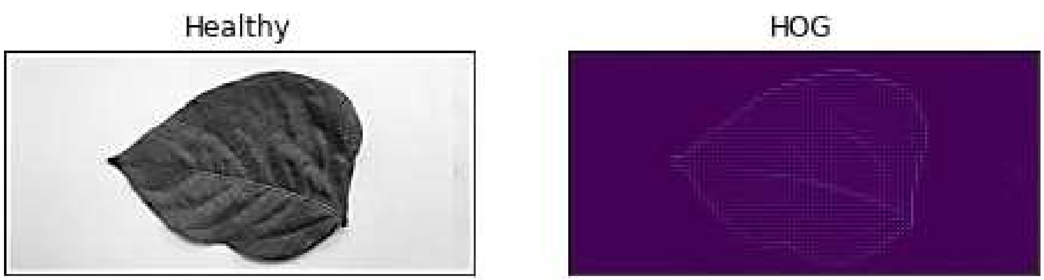
Figure 2: All Categories (Controlled Environment)

4.2 Preprocessing

In this study SVM and ConvNets are built with different model architectures and hence need to implement different preprocessing steps. The image first needs to be read into a three-dimensional NumPy array and rescaled to one-third its size to train an SVM. In Computer Vision, the Histogram of Object Gradients (HOG) is used for object detection. HOG act as feature descriptors by focusing on the shape or structure of the object. In the end, a histogram is created for each local region of the image.



(a)



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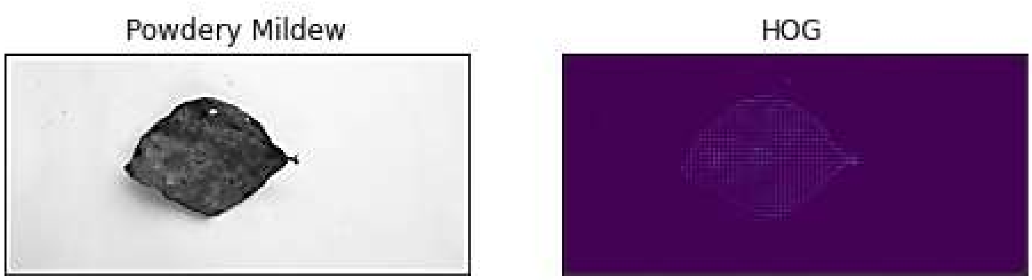

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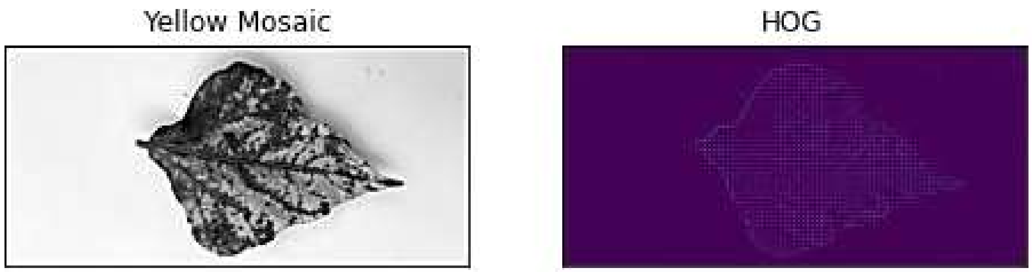


(d)

Figure 3: A leaf image after applying HOG: (a) Cercospora Leaf Spot, (b) Healthy, (c) Powdery Mildew, (d) Yellow Mosaic Virus

The image is converted to grayscale before applying this method. Mapping of the label is done using integers 1 through 4. Figure 3 displays a converted grayscale leaf image and HOG image.

Before applying this technique, we change the leaf image to grayscale. As we are using Sklearn's SVM, so there is no need to hot encode the training labels. Labels are mapped here to the integers 1 through 4.

When using ConvNets, low preprocessing steps prove to be sufficient to get decent results. The image is first read into a 3-dimensional NumPy array and then resized to a size of 256 x 256 pixels. Data normalization ensures that each pixel of the image has a similar data distribution and helps to converge faster while training the model.

4.3 Data Augmentation

A ConvNet is said to have invariance when it is robust enough to classify objects even in different orientations. A model can be trained to be invariant to size, translation, and even illumination. We can generate additional synthetically modified data to train our network prediction accurately in various conditions. This is known as Data Augmentation. It involves augmenting the datasets with perturbed versions of themselves. Various Augmentation properties are applied to the dataset to create new images. This paper used a variety of image enhancement techniques for enhanced image data. Table 1 shows various augmentation properties applied to the dataset.

Table 1: Data Augmentation Property

Property	**min**	**max**
Width Shift Range	0	0.2
Height Shift Range	0	0.2
Brightness Range	0.8	1.2
Zoom Range	0	0.3
Flip	Horizontal	Vertical

5. TRAINING PROCESS

5.1 Support Vector Machine

An SVM is capable of providing high accuracy compared to other machine learning models like logistic regression etc. To handle nonlinear input spaces, the SVM uses a kernel trick to map the data to a higher dimension so that it is possible to find a hyperplane that divides the different classes. Sklearn.svm.SVC provides a Support Vector Classifier. An SVC with a polynomial kernel and the regularization parameter C is set on a "One vs. One Strategy". This strategy is a heuristic method to use binary classification on all the classes one by one for multiclass classification. Each binary classification predicts one class label and the model with the most predictions is predicted by the one-by-one strategy. SVM after training yielded a test accuracy of 86.9% but it overfits the dataset and thus was not a reliable model. Figure 4 shows the confusion matrix for 4 Mung leaf categories that include 3 diseased and a healthy category and Table 2 shows the classification report for the controlled environment with SVM.

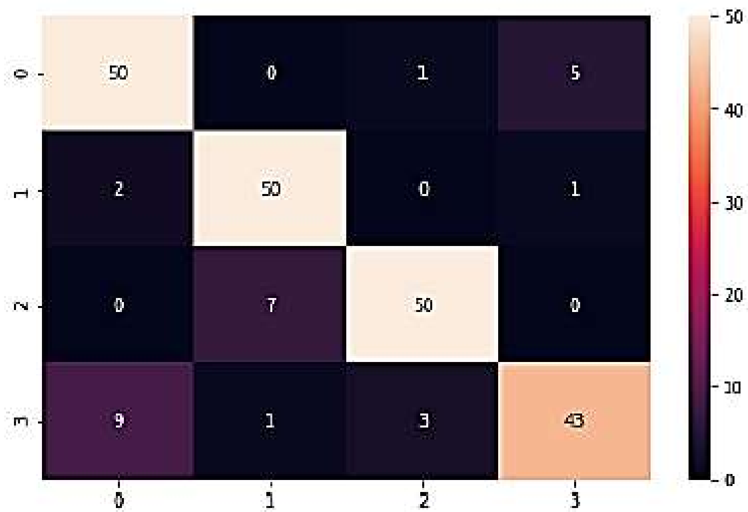


Figure 4: Confusion Matrix (Controlled); 0-Cercospora, 1-Healthy, 2-Powdery Mildew, 3-Yellow Mosaic

Table 2: Classification Report

	precision	**recall**	**f1-score**	**support**
0	0.82	0.89	0.85	56
1	0.86	0.94	0.90	53
2	0.93	0.88	0.90	57
3	0.88	0.77	0.82	56
accuracy			0.87	222
macro avg	0.87	0.87	0.87	222
weighted avg	0.87	0.87	0.87	222
0 – Cercospora		1 – Healthy		
2 – Powdery Mildew		3 – Yellow Mosaic Virus		

To regularize the effect of overfitting, different values for the regularization parameter and other hyperparameters are tried. Grid Search is used to find the hyperparameters that yield better accuracy and do not overfit. Various hyperparameters like C, Gamma, Kernel, Degree, and Strategy with a set of values are applied on Grid Search with 5-fold cross-validation.

Training accuracy of the model reached 100% and test accuracy fell to 86.4% when the results of the grid search were applied.

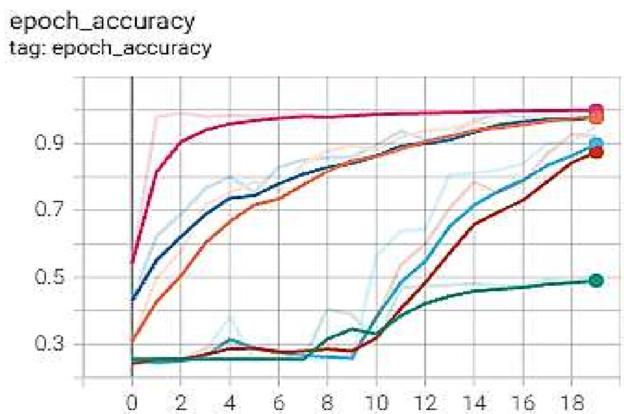
5.2 Convolutional Neural Networks

CNN models with different architectures are trained to complete our objective. The comparison process is divided into 2 different rounds. A batch size of 64, input shape (256, 256, 3), and a learning rate of 0.0003 are maintained throughout the comparison. In the first round, a custom CNN architecture and two pre-built models: VGG16 and MobileNetV2 are compared with each other. In the convolutional layer, the padding "same" is applied in all three models. Except for the Custom CNN, the pre-trained weights for the other models are loaded and thus its training process is Transfer Learning. All three models are trained for 20 epochs and categorical cross-entropy as their loss function. MobileNet V2 model performs very poorly and also overfits the dataset with a huge difference. On the other hand, the VGG16 architecture performs the best with a test accuracy of 95.5%. Our Custom CNN model also performs decently with a test accuracy of 89.9% but can still be improved by hyperparameter tuning. Data Augmentation did not positively affect the training process and thus is not applied in the training process. Table 3 displays Custom CNN model architecture.

Table 3: Model Architecture (Custom CNN)

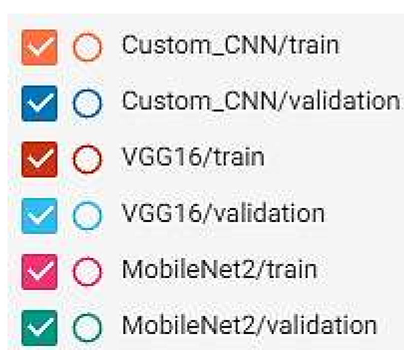
Layer	**Filters**	**Kernel**	**Act.**	**MP**
Conv2D	32	3 x 3	ReLU	✔
Conv2D	64	3 x 3	ReLU	✔
Conv2D	128	3 x 3	ReLU	✔
Conv2D	128	3 x 3	ReLU	✔
Conv2D	256	3 x 3	ReLU	✔

Layer	**Neurons**		**Act**	
Flatten	-	-	-	-
Dense	256	-	ReLU	-
Dense	128	-	ReLU	-
Dense	128	-	ReLU	-
Dense	64	-	ReLU	-
Dense	4	-	Softmax	-



(a)

(b)



(c)

Figure 7: (a) Accuracy Graph for Custom CNN, VGG 16, and Mobilenet V2 for train and validation, (b) Loss Graph for Custom CNN, VGG 16, and Mobilenet V2 for train and validation, (c) Legends

Here, Figures 5 and 6 displays accuracy and loss graphs. The accuracy and loss comparison is displayed in below table 4.

Table 4: Accuracy and Loss Metrics in the first round

Model	Accuracy (%) (Train / Test)	Loss (Train / Test)
Custom CNN	96.67 / 89.19	0.1006 / 0.2553
VGG16	93.65 / 95.5	0.2182 / 0.1487
MobileNet V2	99.8 / 35.14	0.0001 / 29.7

In the second round, we try to tune the hyperparameters of the custom CNN model to yield the best results we could. The following parameter grid combination is used to search for the best hyperparameters:

Table 5: Parameter grid (controlled – CNN)

Batch Norm.	{True, False}
Optimizer	{SGD, RMSprop, Adagrad, Adadelta, Adam, Adamax}
Learning Rate	{0.01, 0.03, 0.001, 0.003, 0.0001, 0.0003 }
Dropout rate	{0.0, 0.1, 0.2}

After performing the hyperparameter tuning using Keras-tuner, we found that the best hyperparameter for our Custom CNN model was:

Batch Norm. – False **Optimizer – Adamax**
Dropout rate – 0.1 **Learning rate – 0.0003.**

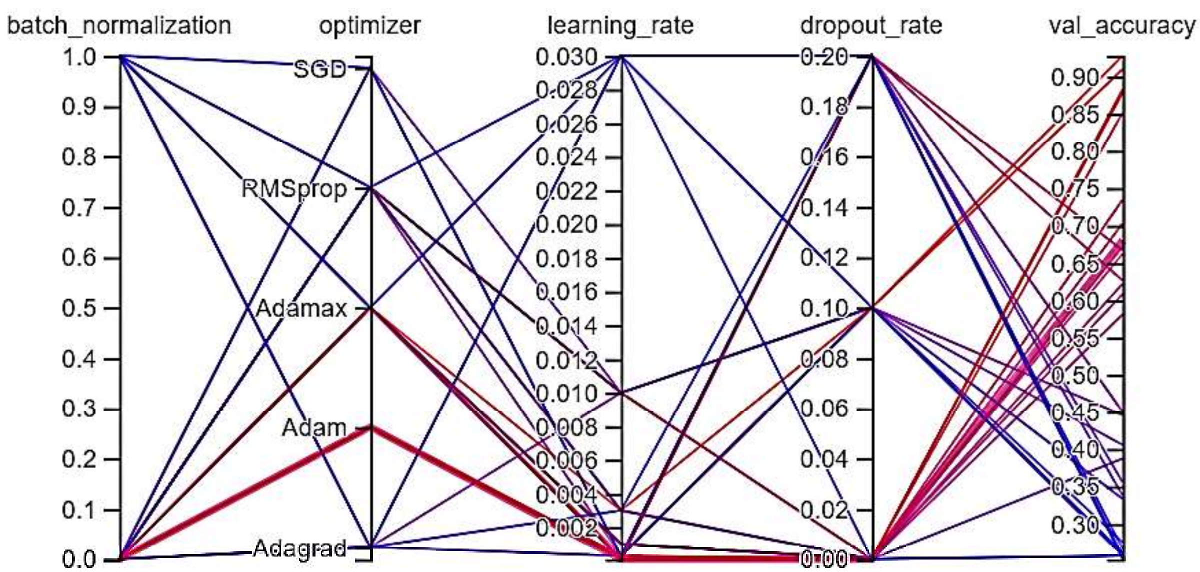
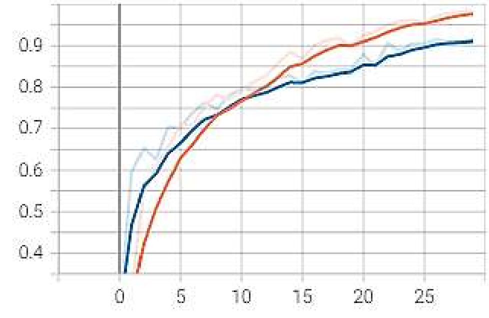
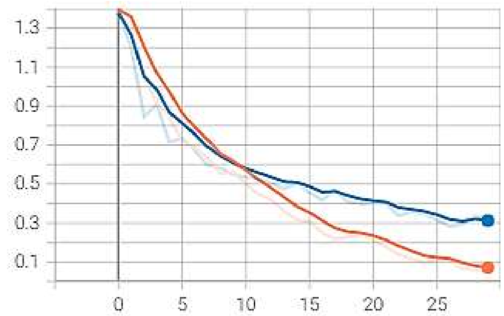


Figure 8: Keras Tuner Results (Controlled - CNN)

The CNN model has trained again but with the given hyperparameters and yields a training accuracy of 97.67% and testing accuracy of 91.03%. Figures 9 represent the accuracy and loss graphs for training and validation.



(a)



(b)

(c)

Figure 9: (a) Accuracy Graph for Custom CNN, (b) Loss Graph for Custom CNN, (c) Legends

6. CONCLUSION

In the controlled environment, even after applying high regularization, the SVM overfit the data. Due to the lack of sufficient data to train the model, it overfits. In machine learning, a huge sample of data is needed to decently predict any activity. CNN proved to be robust in a Controlled Environment despite the lack of huge amounts of data. They successfully captured features from the image and classified them with a test accuracy of 95.05%.

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EARLY RECOGNITION OF MUNG LEAF DISEASES BASED ON SUPPORT VECTOR MACHINE AND CONVOLUTIONAL NEURAL NETWORK

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Abstract. This paper proposed a model that Classifies a Mung (Vigna mungo L.) leaf to check if it is healthy or infected with a disease with the aid of Machine Learning and Deep Learning algorithms. The dataset is created in a controlled environment, where a controlled environment is a data item (image) that comprises only a single subject (leaf) and a white background collected from the south Gujarat Region in India. SVM and CNNs with different architectures have been trained and compared to each other. It aimed at detecting 3 mung leaf disease categories and a healthy leaf category. The model extracts complex features of various diseases. Comparative experiment results show that in the proposed work SVM overfit the data and CNN achieves 95.05 percentage of identification accuracy on the Mung leaf image dataset. Early detection will help farmers to improve their productivity. The main objective was to automate Mung Leaf disease identification using advanced deep learning approaches and image data.

Keywords: Mung leaf, Classification in Machine Learning, SVM, Deep Neural Networks, Convolutional Neural Networks.

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1 Introduction

Mungbean is also known as green gram which is a highly nutritious legume crop and considered as a quality pulse due to its rich protein content and excellent digestibility. India is the largest producer of mungbean where it is the third most important pulse crop with an area of approximately 34.50 lakh hectares with 15.91 lakh tonnes of total production [32]. To meet global demand, it is commanding to increase the current average global productivity [23]. Having diseases in plants is a natural process. In traditional practice, farmers try to evaluate the diseases by their past experience. Or in other cases, the expert observes the plant organs like leaves and stems for any diseases. It is a very time-consuming and costly method because it requires continuous monitoring by an expert in large fields. Early identification and treatment will help farmers to reduce the overall loss. We require a fast approach to protect the crop from diseases. Using advanced technology like mobile phones, tablets, and similar devices farmers can input data in form of digital images and get an immediate response. That will result in crop productivity. We need automated approaches that can support farmers in the early detection and prevention of Mung leaf diseases. Machine Learning and Deep Learning are part of Artificial Intelligence that emphasizes making predictions using algorithms that increase automatically through experience and by the use of data. Algorithms build an inference model based on training data to generalize the context and make predictions. Different deep learning models such as VGG16, MobileNetV2, and

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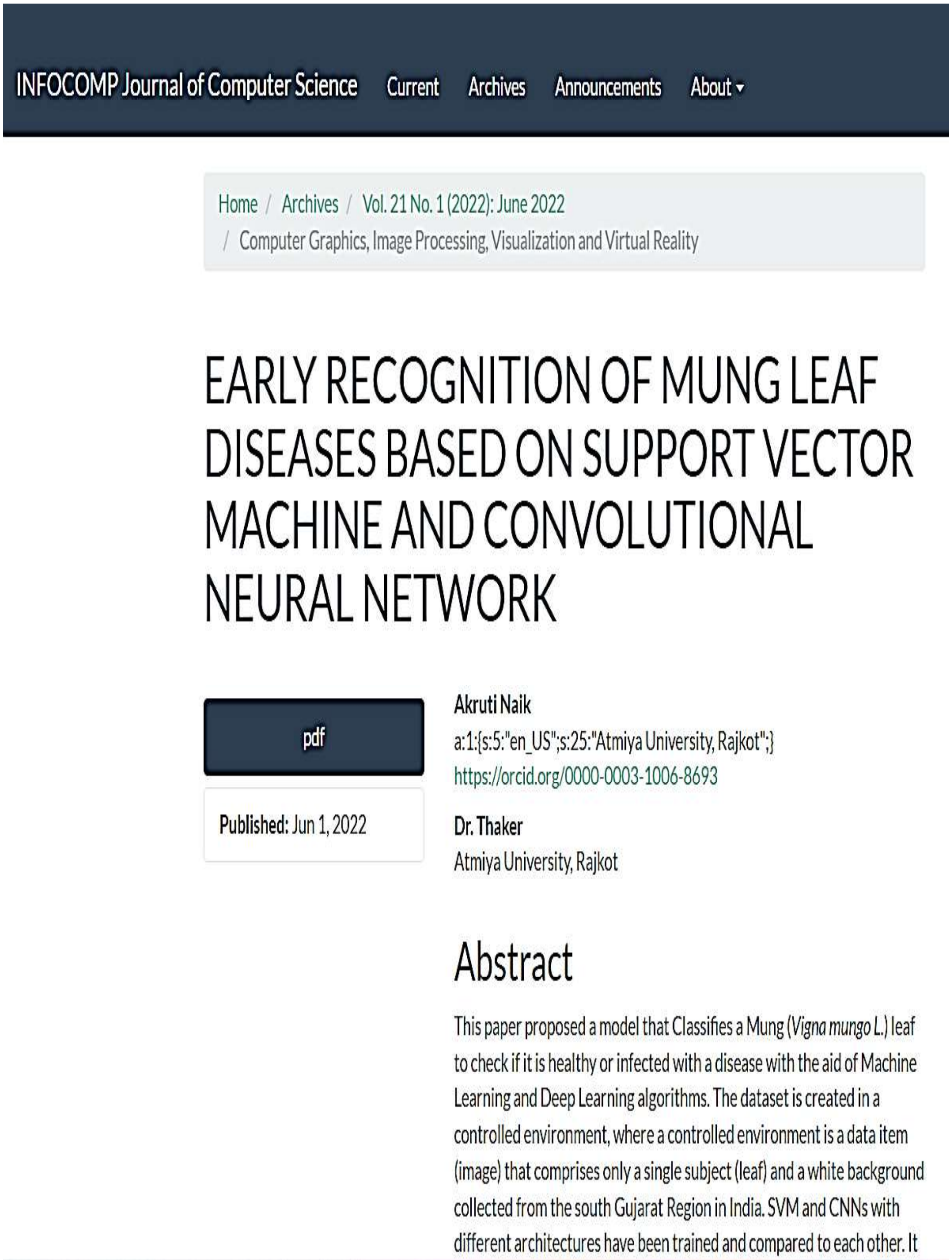
Figure 14: First Page of published paper



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EARLY RECOGNITION OF MUNG LEAF DISEASES BASED ON SUPPORT VECTOR MACHINE AND CONVOLUTIONAL NEURAL NETWORK

pdf

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Abstract

This paper proposed a model that Classifies a Mung (*Vigna mungo L.*) leaf to check if it is healthy or infected with a disease with the aid of Machine Learning and Deep Learning algorithms. The dataset is created in a controlled environment, where a controlled environment is a data item (image) that comprises only a single subject (leaf) and a white background collected from the south Gujarat Region in India. SVM and CNNs with different architectures have been trained and compared to each other. It

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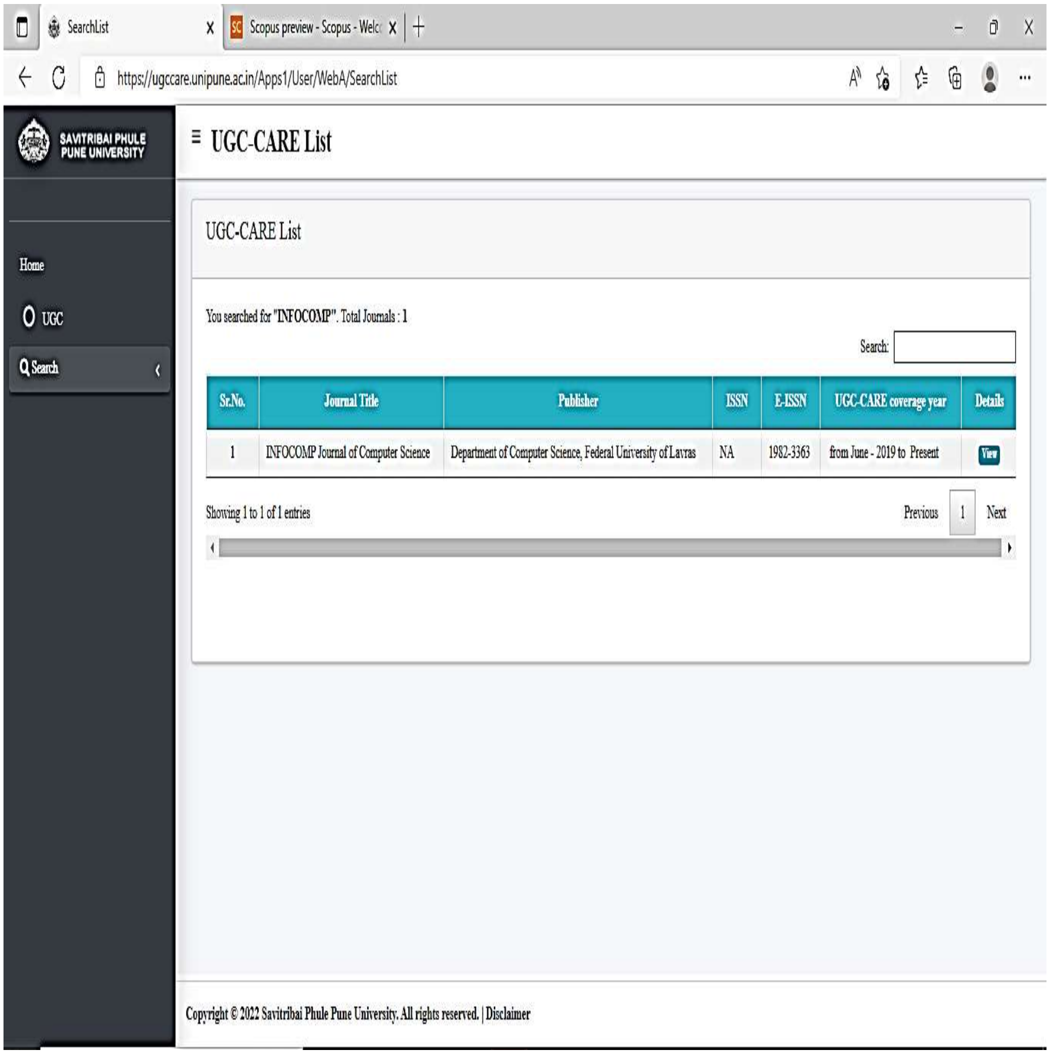

Figure:UGC care list

Appendix – A (3)

1. 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, Image analysis, Image Dataset, Disease Identification, Pre-processing, Segmentation.

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.

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.

Table 1. Summarizes the researches carried out in recent times

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)	Multi Species	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.

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.

Table 2. 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

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 bean plant organs.

MATERIALS AND METHODS

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

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.

1.1.1 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.

1.1.1.1 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

1.1.1.2 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.

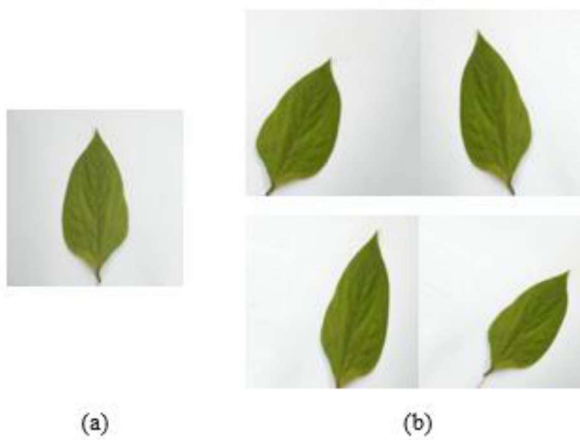

Fig. 4. (a) Original Image, (b) Augmented images

1.1.2 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.

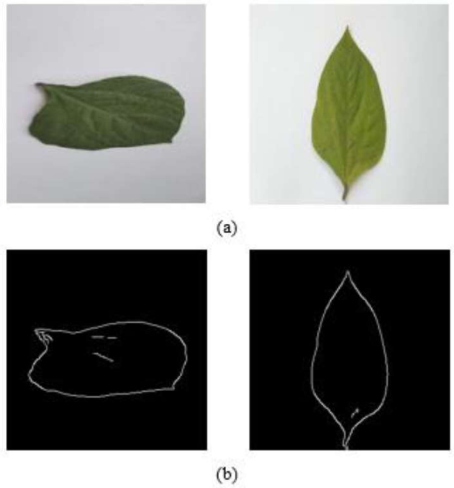

Fig. 5. (a) Original images, (b) Extraction of Boundary

1.1.1.3 Steps for segmentation

.

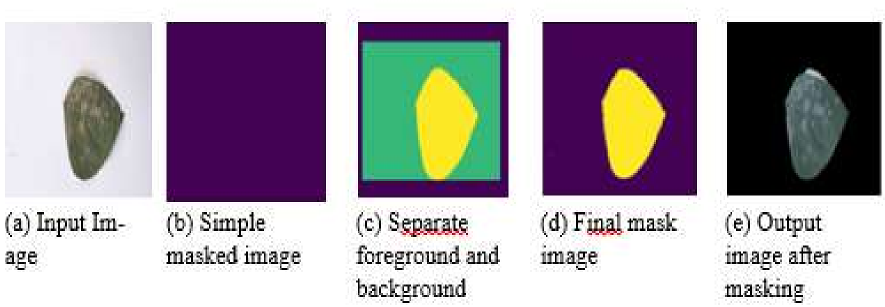

Fig. 6. Segmentation Process

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.

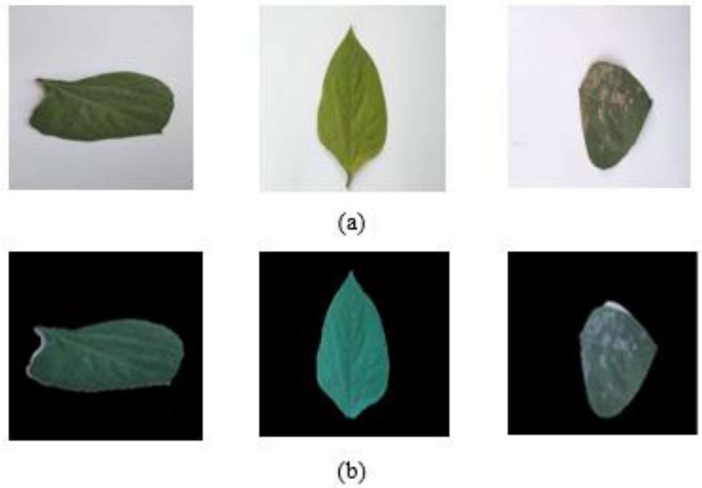

Fig. 7. (a) Original Images, (b) Segmented Images

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.

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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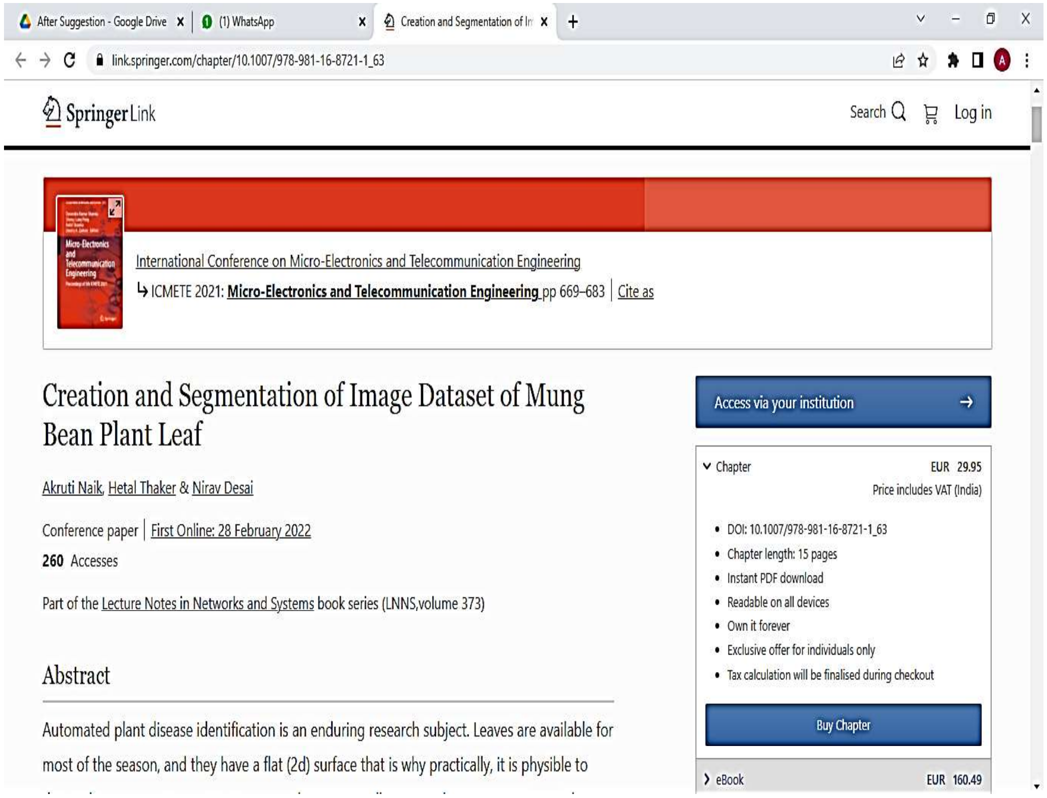

Figure: Journal Link

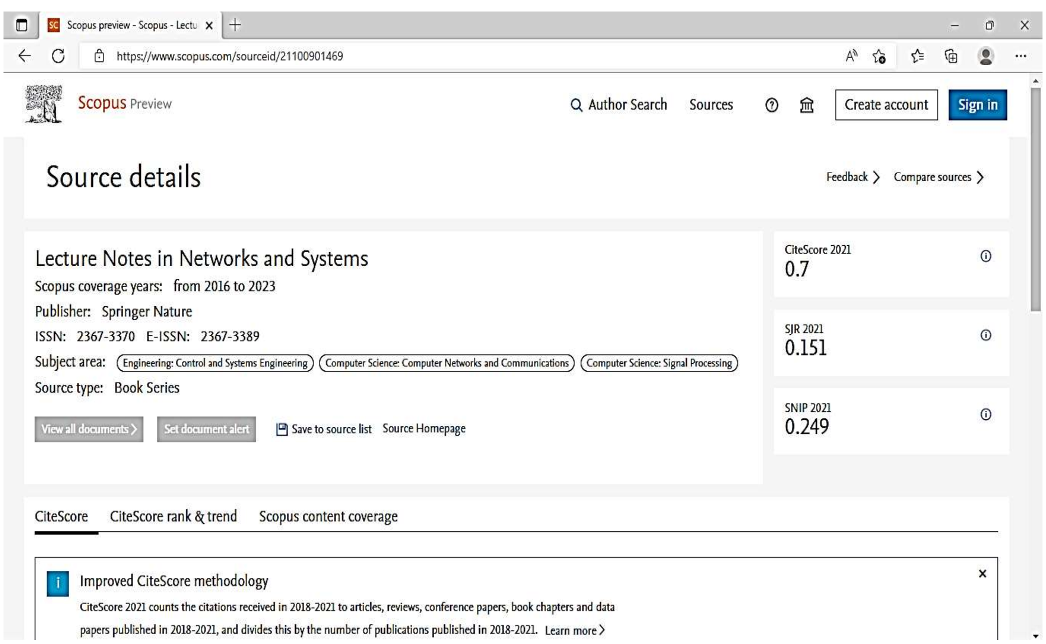

Figure: Scopus Coverage

Appendix – B (1)

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International Research Conference on IoT, Cloud and Data Science (IRCICD'21)

Certificate of Participation

This is to certify that

Ms. AKRUTI NARENDRAKUMAR NAIK

ATMIYA UNIVERSITY

has participated and presented a paper titled

CREATION AND SEGMENTATION OF IMAGE DATASET OF MUNG BEAN PLANT LEAF

in the Virtual International Research Conference on IoT, Cloud and Data Science (IRCICD'21) Organised by the Department of Computer Science and Engineering, SRM Institute of Science and Technology, Vadapalani, Chennai, Tamil Nadu, India held on 23rd and 24th April 2021.

M. Durgadevi	G. Paavaianand	S. Prasanna Devi		
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Figure: Certificate of journal publication

Appendix – B (2)


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is awarded to

Naik Akruti Narendrakumar

for presenting a paper titled

Early Recognition Of Mung Leaf Diseases Based on Support Vector Machine And Convolutional Neural Networks In Uncontrolled Environment

in **'International Conference on Emerging Trends & Contemporary Practices 2022'**, organized by Atmiya University, India on 19th & 20th May, 2022, in association with University of Miyazaki (Japan), Keck Graduate Institute (USA), Lincoln University College (Malaysia) & Hemchandracharya North Gujarat University (India)

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Summary

Introduction

Agriculture field plays an important role in economy of any country. As India is one of the developing country agriculture is one of the backbone of economy. Having diseases in plants is a natural process. In traditional practice farmer try to evaluate the diseases by his past experience. Or in other case the expert observe the plant organs like leaves and stems for any diseases. It is very time consuming and costly method. We require an early identification to protect crop from diseases. This study perform classification techniques to identify mung bean plant leaf diseases using machine learning and deep learning techniques.

Chapter 1 Introduction to Plant Disease Detection System

This chapter gives overview of the research work, its scope, objectives, need etc. in detail. Also chapter covers details of common mung bean plant diseases and diseases covered in this study. Application area of agriculture image processing, Crop/Plant diseases selection, image processing techniques are also covered in this chapter. The summary of the overall thesis is also discussed.

Chapter 2 Literature Review

Study of the previously done work up to now in the area of plant disease recognition for numerous plants and its organs is discussed in this chapter. It includes journal articles, conference articles, electronic documents, web resources.

Chapter 3 Plant Foliar Disease Identification Model

In this chapter design of the foliar/leaf disease detection model is discussed in detail. Numerous components and subcomponents of model are explained in detail in this chapter.

Chapter 4 Development of Plant Foliar Disease Identification Model (PFDIM)

This chapter describes component development of the model presented in chapter 3 in detail. Input and output of the model "Plant Foliar Disease Identification Model" is discussed in this chapter.

Chapter 5 Results and Conclusion

This chapter converses result of the projected PFDIM model applied on mung leaf dataset collected to quantity the success of projected research work. Moreover this chapter presents conclusion of projected research work along with path for future scope in the present research space.

Conclusion

Results and conclusion are discussed in detail in chapter 5 based on various parameters. This chapter presented the results concerning to the numerous proposed models.