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Classification of Microscopic Images of Fungi Using Deep Learning Models

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ABSTRACT

The paper aims to identify the microscopic images of fungi Colletotrichum gloeosporioides and Cylindrocladium colhounii, which affect the leaves of Mango and Custard apple plant. The affected leaves are collected, cultivated and observed under high power 40X objective lens. The collected dataset is brand new of 78 images and feed to the two pre-trained deep learning models AlexNet and SqueezeNet. We propose an idea of identifying these fungi at microscopic level, where not much of work is done on fruit plants of Hyderabad and Karnataka (H&K) region of Karnataka, India. Using the CNN models, performance measures such as mean precision, mean recall, F1 score and accuracy are calculated and it is observed that AlexNet model gives a good recognition accuracy of 93.8% compared to the SqueezeNet model. **Keywords**: Microscopic images, Fungi detection, CNN, AlexNet, SqueezeNet.

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INTRODUCTION

NDIA is a country where most of the population depends on agriculture as the major source of income. Fruits being a part of the human diet play a role in balancing the diet of our body. Due to increase in demand of fruit supply, there is a need to produce the fruits as much as needed. But due to environmental conditions, soil, land, virus, fungi etc., leads to the destructions of these plants. Most of fruit plants yield are lost due to fungi, as these require normal temperature to spread from one plant to neighboring. Hence there is a need to detect these fungi at an early stage, so it can be stopped from spreading to the neighboring plant.

In this paper we aim to identify these fungi at microscopic level. We are the first of its kind, to work on fungi affected leaves of fruit plants of mango and custard apple plant. The scientific name of mango is Mangifera indica, which belongs to the cashew family. The fruit is rich in vitamin A, C and D. The fruit has a mix taste of Oranges, Peaches and

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Pineapples; hence it is known as "King of Fruit". India is the top producer of Mangoes. It doesn't require any special soil and temperature to grow hence it is widely grown throughout India. The common diseases of mango plant are Powdery Mildew, Anthracnose, Alternaria leaf spot, Bacterial canker, Die back, Gummosis and Root rot [1]. Most of these diseases are affected by fungi. Hence there is a need to work on fungi affected leaf diseases.

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The scientific name of custard apple plant is Annona squamosa. The fruit has flesh which is creamy, smooth, rich and sweet in taste. Many farmers pick these fruits before they are fully ripe as they continue to ripe once they are picked from the tree. These are perishable fruits, lasting only a week at room temperature. The fruit is rich in B6, omega 3s, phosphorous and manganese. The common diseases of Custard apple plant includes Anthracnose, leaf spot, Diplodia rot, Black canker, Spiral nematode and Stunt nematode [2].

The disease symptoms and the area of the affected leaf determine the type of disease. To recognize these diseases there needs to be continuous and frequent monitoring of the plants by plant pathologists or the farmers, which is tiresome and expensive method as they need to travel far from places to the farm and sometimes it may lead to wrong assumptions of the diseases. Hence we try to develop a fast, accurate, automatic, affordable and easily available technology. This is possible through the Computer vision, Pattern recognition, Image processing, Machine learning and Deep learning technologies which are research attraction in the current scenario.

We aim to work on microscopic images of these fungi affected leaves of mango and custard apple. The dataset collected is brand new and is not publically available yet.

The remaining of the paper is organized as Section 2 narrates the survey of literature, Section 3 describes the collected dataset, Section 4 describes projected approach using different models and classifiers, Section 5 deals with the experimental results and in Section 6 conclusions are summed up.

LITERATURE SURVEY

Table-1: Survey of Identification And Classification of Microscopic Images

SI. No.	Name	Dataset used	Method used	Class labels	Obtained accuracy
1	Muhammad Waseem Tahir et.al,[3]	Own fungus spores dataset	Customized CNN architecture	5 different classes of fungi	94.8%
2	Anuruk Prommakhot et.al, [4]	Own fungus spores dataset	Customized CNN architecture	2 different classes of fungi	98.03%
3	Lin Liu et.al, [5]	Own fungus spores dataset	ANN architecture	1 class, identifying the image has fungi or not	Model gives good result

From Table-2 it is evident that authors have worked only on leaf diseases caused by various bacteria, algae and other factors. No one has worked on microscopic images of fungi affected diseases. Table-1 depicts classifying different types of fungi, which are obtained through soil, contaminated food, human body, air borne fungi etc. No author has worked on microscopic images of fungi affected leaf diseases.

We are the first of its kind to work on fungi affected plant leaf diseases. We properly cultivate the medium of PDA (Potato Dextrose Agar) to obtain the microscopic images of two kinds of fungi i.e., Colletotrichum gloeosporioides Cylindrocladium colhounii fungi.

Authors have worked on Customized Convolutional Neural Network (CNN). We try to experiment on pretrained Deep learning architectures such as AlexNet and SqueezeNet, to know the efficiency of pretrained architectures.

The authors in Table-1 & 2 have used different methods to pre-process the images to increase the recognition accuracy of their models. But to reduce the space and time complexity we have eliminated the step of pre-processing. The taken 78 images are resized to size 227x227x3 for the uniformity of the model.

OVERVIEW OF DATASET

A genuine database is needed to evaluate the execution of CNN architecture. We have collected our own new dataset of microscopic images. The dataset consists of two categories of fungi affected images, one is Colletotrichum gloeosporioides fungi which cause Anthracanose in Mango plants, and another is Cylindrocladium colhounii fungi which causes leaf spot in Custard apple plant.

Total of 78 images i.e., 39 images from each class label are taken for experimentation purpose. The dataset is divided into 80:20 split, 80% is used for training purpose and the rest is utilized for validation. Two Deep learning models AlexNet [10] and SqueezeNet [11] are utilized to measure their performance. Below Table-3 shows the overview of our dataset.

Table-3: Summary of Microscopic Images

Name	Training Images	Testing Images	Total Images
Mango	27	12	39
Custard apple	27	12	39
Total	54	24	78

Below Fig 1 and 2 shows the microscopic images of fungi Cylindrocladium colhounii of Custard apple and Colletotrichum gloeosporioides fungi of mango plant respectively.

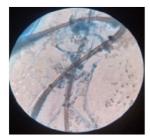


Figure1: Cylindrocladium colhounii

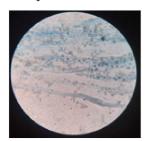


Figure 2: Colletotrichum gloeosporioide

Table-2: Survey of Identification and Classification of Leaf Images

SI. No.	Authors	Dataset used	Method used	Class labels	Obtained accuracy
1	Xihai Zhang et.al.,[6]	Maize leaves collected from different sites like Plant village, Google websites.	GoogLeNet model &Cifar 10 model	9 different class labels	98.8% using GoogLeNet and 98.9% using Cifar 10 model
2	Mohanty SP et.al.,[7]	Plant Village dataset	AlexNet model &GoogleNet model	38 different class labels	85.53% using AlexNet and 99.34% using GoogLeNet model
3	H. Durmuşet.al.,[8]	Plant Village dataset of only Tomato plant	AlexNet model &SqueezeNet model	10 different class labels	95.6% using AlexNet and 94.3% using SqueezeNet model
4	S. Arivazhagan <i>et</i> .al.,[9]	Collected their own dataset of Mango plant	CNN model	6 different class labels	96.67% using CNN model
5	Sun Xiaoxiaoet.al., [10]	Collected their own dataset of Tea plant	CNN model, SVM and BP	7 different class labels	93.75 % using CNN model, 89.36% using SVM and 87.69% using BP
6	M. R. Howlader <i>et.al</i> .,[11]	Collected their own dataset of Guava plant	D-CNN model	4 different class labels	98.74% using D- CNN model
7	Gaikwad, Sukanya S et.al.,[12]	Plant pathology dataset of Apple plant	CNN model	4 different class labels	88.9% using CNN model
8	MelikeSardog anet.al.,[13]	Dataset of Tomato plant	CNN model with LVQ algorithm	5 different class labels	86% using CNN with LVQ algorithm
9	R. A. Sholihati <i>et.al.,</i> [14]	Collected their own dataset of Potato plant and also from Plant Village and Google	VGG 16 AND VGG 19	5 different class labels	91% using VGG 16and 90% using VGG 19
10	Rangarajanet. al.,[15]	Plant Village dataset of only Tomato plant	AlexNet model and VGG 16	7 different class labels	97.49% using AlexNet and 97.29% using VGG 16

PROPOSED METHOD

We aim to obtain our brand new dataset of microscopic images of fungi, as fungi are responsible for losing half of the produced yield from plants. The step by step process to obtain the microscopic images is noted below

- 1. We collect the fungi affected leaves of both plants i.e., Anthracanose of Mango and Leaf spot of Custard apple plant.
- 2. A Potato Dextrose Agar (PDA) medium is prepared to cultivate the fungi from leaves.
- 3. The collected leaves are washed properly with distilled water, and kept aside.
- 4. Potato infusion of 100gm is prepared as below
 - Take 100gm of sliced potato and boil in 1 liter of distilled water for half an hour.
 - Filter the obtained mixture using cheesecloth, saving the potato infusion.
 - Take a flask add Dextrose, Agar and the saved effluents,
 - Autoclave for 15min at 121° C.
 - Dispense 15-20 ml portions into sterile 100x100 petri dishes.
 - The final pH should be 5.6±0.2.
 - The Table-4 below shows the compositions of PDA.

Table-4: Composition of PDA

Potato infusion	100 gm
Dextrose	2 gm
Agar	2 gm
Distilled water	1 liter

- 5. Cut the affected part of the leaves and inoculate it into the prepared medium.
- 6. Wait for 2 days to let the fungi grow on the medium.
- 7. Take a sterile slide add a drop of Lacto phenol Cotton Blue reagent.
- 8. Sterilize the needle and cool it.
- 9. Transfer the mycelia mat on fluid and press gently so that it easily mixes with the stain.
- 10. Place the cover slip on the preparation, wait for about 5minutes.
- 11. Observe the slide under the microscope with high power 40X objective lens.

12. Fungal spores and hyphae are observed, of which images are captured with 12 Megapixel camera.

The obtained dataset is used for experimentation purpose. Two pre-trained deep learning architectures AlexNet and SqueezeNet are used to evaluate the performance of the dataset. The below figure 3 and 4 shows the layer architecture of AlexNet and SqueezeNet respectively.

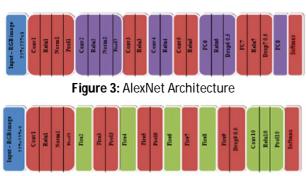


Figure 4: SqueezeNet Architecture

EXPERIMENTAL RESULTS

In this section, we evaluate the experimental results of basic Deep Learning models which are AlexNet and SqueezeNet. The dataset consists of 78 images. The experiment conducted divides the dataset into 80:20, where 80% of data is used for training and the rest 20 % is used for testing purpose. The Table V shows the hyper parameters which are kept same for both the models, to know which model performs the best.

Table-5: Hyper Parameter Tuning

SI. No.	Name of the parameter	Parameter
1	Solver type	Adam Optimizer
2	Base learning rate	0.0001
3	Batch size	64
4	Epochs	25
5	Training data	80%
6	Testing data	20%

Below Table-6 &7 shows the class wise recognition accuracy of AlexNet and SqueezeNet model.

Table-6: Class Wise Recognition Accuracy of AlexNet

SI. No.	Class Name	Accuracy in %
1	Mango	87.5%
2	Custard apple	100%

Table-7: Class Wise Recognition Accuracy of SqueezeNet

SI. No.	Class Name	Accuracy in %
1	Mango	87.5%
2	Custard apple	87.5%

Below Table-8 and Table-9 shows the Confusion matrix for AlexNet and SqueezeNet model.

Table-8: Confusion Matrix of AlexNet

Mango		Custard apple	
Mango	7	1	
Custard apple	0	8	
Accuracy in %		93.8%	

Table-9: Confusion Matrix of SqueezeNet

	Mango	Custard apple
Mango	7	1
Custard apple	1	7
Accuracy in %		87.5%

Below figure 5 shows the comparative analysis of AlexNet and SqueezeNet model.

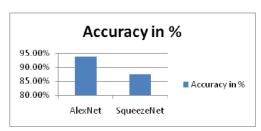


Figure 5: Comparative analysis of AlexNet and SqueezeNet model.

Experimental Evaluation

The evaluation of the learning models is estimated by differentiating already trained models with varying metrics. It is analyzed by how good they perform on a validation dataset. The different performance measures include Precision, Recall and F1 score.

Precision: It is calculated as how much was correctly distinguished as positives out of all positives. It is given by the equation (1).

Precision = True Positive / (True Positive + False Positive) (1)

Sensitivity (Recall): It is the proportions of how many were rightly recognized to how many were true positive. It is given by the equation (2).

Sensitivity = True Positive / (False Negative + True Positive)

F1 Score: It is to compute the performance of the classifier's classifying capacity. It is considered as the superior measure of the model's performance than the regular accuracy measure. It is given by the equation (3).

F1 score = 2 * (Precision * Recall) / (Precision + Recall)

Below Table 10 shows the calculated performance measures of the models.

Table-10: Performance Measures: Precision, Recall, F1 Score Using Transfer Learning

Transfer Learning					
Precision Recall F1score Accuracy					
AlexNet	0.9685	0.9336	0.9560	93.8%	
SqueezeNet	0.9013	0.8839	0.8925	87.5%	

It is observed from Tables 5-9 that the AlexNet model gives good recognition accuracy and performance measures in Table-10 shows that it accomplished better results than SqueezeNet model on the collected real time environment dataset.

CONCLUSIONS

The objective of our paper is to collect the brand new dataset of microscopic images of fungi affected leaves of Mango and Custard apple plant. The novelty of our work is that we experiment on our own collected dataset. This is the first of its kind work, where fungi affected leaves are collected and then cultivated on PDA medium. The developed fungi are observed under microscope of high power 40X objective lens. We evaluate the obtained dataset using the two pre-trained deep learning architectures i.e., AlexNet and SqueezeNet. The hyper parameters of the models are kept same to analyze the performance. Based on the performance measures such as mean precision, mean recall, F1 score and accuracy obtained, it is observed that AlexNet model performed well and achieved a good recognition accuracy of 93.8%.

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REFERENCES

- https://www.krishisewa.com/articles/disease-[1] management/731-major-diseases-of-mango-andtheir-management.html
- [2] https://vikaspedia.in/agriculture/cropproduction/integrated-pest-managment/ipm-forfruit-crops/ipm-strategies-for-custard-apple/ custard-apple-diseases-and-symptoms
- [3] Muhammad Waseem Tahir, Nayyer Abbas Zaidi, Adeel Akhtar Rao, Roland Blank, Michael J. Vellekoop and Walter Lang, "A Fungus Spores Dataset and a Convolutional Neural Network Based Approach for Fungus Detection", IEEE Transcation on Nanobioscience, 2018.
- [4] Prommakhot, Anuruk, and JakkreeSrinonchat. "Exploiting Convolutional Neural Network for Automatic Fungus Detection in Microscope Images." In 2020 8th International Electrical Engineering Congress (iEECON), pp. 1-4. IEEE, 2020.
- Zieliński B, Sroka-Oleksiak A, Rymarczyk D, [5] Piekarczyk A, Brzychczy-W³och M (2020) Deep learning approach to describe and classify fungi microscopic images. PLoS ONE 15(6):2020.
- Xihai Zhang, YueQiao, FanfengMeng, Chengguo Fan, [6] and Mingming Zhang. Identification of maize leaf diseases using improved deep convolutional neural networks. IEEE Access, 2018.
- Mohanty SP, Hughes DP and Salathé M (2016) Using [7] Deep Learning for Image-Based Plant Disease Detection. Front. Plant Sci. 7:1419. doi: 10.3389/ fpls.2016.01419
- H. Durmuþ, E. O. Güneþ and M. Kýrcý, "Disease [8] detection on the leaves of the tomato plants by using deep learning," 2017 6th International Conference on Agro-Geoinformatics, 2017, pp. 1-5, doi: 10.1109/Agro-Geoinformatics.2017.8047016.
- [9] S. Arivazhagan, S. VinethLigi.: Mango Leaf Diseases Identiûcation Using Convolutional Neural Network, International Journal of Pure and Applied Mathematics, Volume 120 No. 6 August – 2018.
- Sun, Xiaoxiao, Shaomin Mu, YongyuXu, Zhihao Cao, [10] and Tingting Su. "Image recognition of tea leaf diseases based on convolutional neural network." arXiv preprint arXiv:1901.02694, 2019.
- [11] M. R. Howlader, U. Habiba, R. H. Faisal and M. M. Rahman.: Automatic Recognition of Guava Leaf Diseases using Deep Convolution Neural Network, 2019 International Conference on

- Electrical, Computer and Communication Engineering (ECCE), Cox'sBazar, Bangladesh, pp. 1-5, April - 2019.
- Gaikwad, Sukanya S. "Fungi Classification using [12] Convolution Neural Network." Turkish Journal of Computer and Mathematics Education (TURCOMAT) 12.10 (2021): 4563-4569.
- MelikeSardogan, AdemTuncer and YunusOzen, [13] "Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm", 3rd International conference on Computer Science and Engineering, pp. 382-385, 2018.
- R. A. Sholihati, I. A. Sulistijono, A. Risnumawan and [14] E. Kusumawati, "Potato Leaf Disease Classification Using Deep Learning Approach," 2020 International Electronics Symposium (IES),2020, pp. 392-397, doi: 10.1109/IES50839.2020.9231784.
- [15] Rangarajan, Aravind Krishnaswamy, Raja Purushothaman, and Aniirudh Ramesh. "Tomato crop disease classification using pre-trained deep learning algorithm." Procedia computer science 133, 2018: 1040-1047.