

Determining Plant Health Using Machine Learning

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ABSTRACT

Crop diseases are a major threat to food security, but their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure. The combination of increasing global smartphone penetration and recent advances in computer vision made possible by deep learning has paved the way for smartphone-assisted disease diagnosis. Using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions, we train a deep convolutional neural network to identify 14 crop species and 26 diseases (or absence thereof). The trained model achieves an accuracy of 99.35% on a held-out test set, demonstrating the feasibility of this approach. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path toward smartphone-assisted crop disease diagnosis on a massive global scale.

1.INTRODUCTION

India is a cultivated country and primarily depends on agriculture. Disease on plant leads to the significant reduction in both the quality and quantity of agricultural products. Identification of the plant diseases is the key to preventing the losses in the yield and quantity of the agricultural product. The studies of the plant diseases mean the studies of visually observable patterns seen on the plant. Health monitoring and disease detection on plant is very critical for sustainable agriculture. It is very difficult to monitor the plant diseases manually. Identification of the plant diseases is the key to preventing the losses in the yield and quantity of the agricultural product. The studies of the plant diseases mean the studies of visually observable patterns seen on the plant product. The studies of the plant diseases mean the studies of visually observable patterns seen on the plant.

Ensuring food security for the growing population is more important for country like India .Most plants are affected by diseases through their leaves. The effectof disease causes color change in leaf. Most of the time the photosynthetic apparatus in chloroplast gets affected due to disease which causes observable color change in leaf. Thus leaf color can be used as the parameter to determine the health of plant.

The main aim of the article is to determine the plant health status by using the color of plant leaf. The details of plant leaf colors are determined using Color sensor which senses the RGB (Red Green Blue) component. The collected data from different leaves are used to train the Machine Learning model that determines plant health status.

2. SYSTEM DESIGN

2.1 FLOWDIAGRAM FOR TRAINING:

The data collected is organized and labeled into healthy and unhealthy. The raw data is labeled because Supervised Machine Learning method is used to determine plant disease detection. The data set is created based on the data collected through sensor and other sources such as Kaggle (Data Science platform supported by Google). The data set is used to train model using appropriate statistical algorithm to identify pattern in the data. After multiple training the model is deployed into a library.



FIG 2.1 FLOW CHART FOR TRAINING MACHINE LEARNING MODEL

2.2 BLOCK DIAGRAM FOR CLASSIFICATION:



FIG 2.2 BLOCK DIAGRAM FOR CLASSIFIACTION OF PLANT HEALTH

The trained and tested Machine Learning library is used to classify the plant health status. The new data collected from sensor is used by the classifier program to fetch results regarding prediction from the Machine Learning library .The prediction is displayed as result by the classifier program

3. PROPOSED SYSTEM

3.1 CIRCUIT DIAGRAM



FIG2.3 CIRCUIT DIAGRAM FOR COLOR SENSING USING APDS 9960 ANDARDUINO UNO

3.2 WORKING:

In our proposed system, the APDS 9960 color sensor determines the RGB component of leaf. The APDS 9960 is moved horizontally in order to cover different parts of leaf. The SPST switch is used to move the sensor horizontally. The data collected through the APDS 9960 is collected by the micro controller and the data taken from the serial monitor is used as the raw data to train the machine learning model. The data collected from multiple leaves and the parameters averaged to obtain the final dataaccording to metrics.

Also data collected from the external sources are organized along with the data collected. Since supervised learning is implemented the data is labelled under different labels such as "healthy" and "unhealthy". The Edge impulse studio is used for training and deploying the model. The uploaded data is then data features are obtained using K-Means Clustering algorithm and the statistical clusters are obtained in graph using Red, Green Blue as the X,Y and Z axis in the three dimensional space. The model is now trained using the above mentioned features and retrained by reducing the learningrate because when the learning rate is slower the model understands better. After training testing is done using existing data to identify the accuracy in prediction. Testing is also done using new data. After testing the model is deployed into a C++ library. The library is used in code to determine the plant health status.

4. RESULTS

The brief information regarding the data collection, training, testing and prediction of the plant health status.

4.1 HARDWARE SETUP



FIG 4.1 HARDWARE SETUP

4.2 DATA COLLECTION FROM HARDWARE

1										
18:36:39.108	->	Ambient:	31	Red:	6	Green:	9	Blue:	12	
18:36:40.131	->	Ambient:	32	Red:	6	Green:	9	Blue:	12	
18:36:41.122	->	Ambient:	32	Red:	6	Green:	9	Blue:	12	
18:36:42.152	->	Ambient:	31	Red:	6	Green:	9	Blue:	11	
18:36:43.138	->	Ambient:	32	Red:	6	Green:	10	Blue	: 13	2
18:36:44.129	->	Ambient:	31	Red:	6	Green:	9	Blue:	11	
18:36:45.168	->	Ambient:	31	Red:	6	Green:	9	Blue:	12	
18:36:46.158	->	Ambient:	31	Red:	6	Green:	9	Blue:	11	
18:36:47.144	->	Ambient:	21	Red:	3	Green:	6	Blue:	8	
18:36:48.166	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:36:49.157	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:36:50.189	->	Ambient:	22	Red:	3	Green:	6	Blue:	9	
18:36:51.175	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:36:52.199	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:36:53.190	->	Ambient:	21	Red:	3	Green:	6	Blue:	8	
18:36:54.175	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:36:55.214	->	Ambient:	21	Red:	3	Green:	6	Blue:	8	
18:36:56.195	->	Ambient:	13	Red:	2	Green:	3	Blue:	5	
18:36:57.186	->	Ambient:	13	Red:	2	Green:	4	Blue:	5	
18:36:58.218	->	Ambient:	13	Red:	2	Green:	4	Blue:	5	
18:36:59.194	->	Ambient:	13	Red:	2	Green:	4	Blue:	5	
18:37:00.217	->	Ambient:	14	Red:	2	Green:	4	Blue:	5	
18:37:01.238	->	Ambient:	17	Red:	2	Green:	4	Blue:	6	
18:37:02.224	->	Ambient:	18	Red:	3	Green:	5	Blue:	7	
18:37:03.249	->	Ambient:	19	Red:	3	Green:	5	Blue:	7	
18:37:04.224	->	Ambient:	17	Red:	3	Green:	5	Blue:	6	
18:37:05.262	->	Ambient:	18	Red:	3	Green:	5	Blue:	7	
18:37:06.236	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:37:07.258	->	Ambient:	22	Red:	3	Green:	6	Blue:	9	
18:37:08.249	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:37:09.280	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:37:10.271	->	Ambients	22	Red:	4	Green	6	Bluer	8	
18:37:11.284	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:37:12.260	->	Ambient:	23	Red:	4	Green:	6	Blue:	8	
18:37:13.291	->	Ambient:	22	Red:	3	Green:	6	Blue:	9	
18:37:14.266	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:37:15.304	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:37:16.294	->	Ambient:	22	Red:	3	Green:	6	Blue:	9	
18:37:17.279	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:37:18.302	->	Ambient:	22	Red:	3	Green:	6	Blue:	9	
18:37:19.293	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:37:20.304	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:37:21.296	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:37:22.318	->	Ambient:	23	Red:	4	Green:	6	Blue:	8	
18:37:23.313	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:37:24.345	->	Ambient:	22	Red:	3	Green:	6	Blue:	9	
18:37:25.329	->	Ambienti	23	Red	4	Green	6	Blues	8	
18:37:26.315	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:37:27.328	->	Ambient:	21	Red:	3	Green:	6	Blue:	8	
18:37:28.360	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:37:29.345	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:37:30.381	->	Ambient:	23	Red:	4	Green:	6	Blue:	9	
18:37:31.367	->	Ambient:	22	Red:	4	Green	6	Blue:	9	
18:37:32.351	->	Ambient:	22	Red:	4	Green:	6	Blue:	8	
18:37:33.348	->	Ambient:	22	Red:	4	Green:	6	Blue:	9	
18:37:34.381	->	Ambient:	21	Red:	3	Green:	6	Blue:	8	
18:37:35.356	->	Ambient:	22	Red:	3	Green:	6	Blue:	9	
18:37:36.374	->	Ambient:	21	Red:	3	Green:	6	Blue:	8	
	-									
Autoscroll] Sh	ow timestamp	2							



FIG 4.2 SAMPLE LEAF DATA 1



FIG 4. 3 SAMPLE LEAF DATA 2

4.3 MACHINE LEARNING TRAINING

C O B studio.edgeim	pulse.com/studio/12179/acquisition/training	'page=1	¢ 0 0 ¢
EDGE IMPULSE	DATA COLLECTED 152 items	4	Record new data
Dashboard			No devices connected to the remote management API.
Devices	Collected data	TB±O	
Data acquisition	SAMPLE NAME LAREL	ADDED LENGTH	3e21011f-edbd-4a4a-ae6d-
Impulse design	3e21011f-edbd-4a unhealthy-vi	Today. 09:59 I	16e08552169aRS_GLSp 7310.JPG.1p9qdnr9
Create impulse.	Scd4836c-b974-42 unhealthy-vi	Today. 09:59 • I	
 image 	4f50bad3-aee2-4 unhealthy-vi	Today. 09:59 • I	414 185
 Transfer learning 	05daf90f-9100-49 unhealthy-vi	Today, 09:59 •	/
 Anomaly detection 	3fefc48b-6431-4c unhealthy-vi	Today, 09:59 • 1	
Retrain model	05f92471-3cd4-44 unhealthy-vi	Today. 09:59 • 8	
Live classification	5afd034f-f65c-4ee unhealthy-vi	Today, 09:59 • 1	
Model testing	Sb6fe4ff-01b0-4b, unbealthy-vi-	Today, 09:59	
Versioning			

FIG 4.4 COLLECTION AND LABELLING OF RAW DATA



FIG 4.5 FEATURE EXTRACT AND CLUSTER VISUALIZATION



FIG 4.6 TRAINING MODEL

	eimpuise.com/s	tudio/12179/validation							\$ C		*
EDGE IMPULSE		This lists all test data. You ca	n manage this (data through Data ac	equisition.						
Dashboard	Te	st data									
Devices											
Data acquisition	Set	the 'expected outcome' for eac	h sample to the	e desired outcome to	automatically sc	ore the impu	lse.	10	CCURACY	8	
Impulse design	(0	assify selected (2)							0.0070		2
Create Impulse											
• image	0	01e94c43-0879-4e8c-9b61	Unhealthy-f	Today, 09:58:58	LENGTH	ANOMALT	ACCOR.	RESULT		1	
Transfer learning	0	1c31a116-f51d-4f56-9c69	Unhealthy-f	Today, 09:58:57					ь	1	
Anomaly detection	2	1c4c2235-2c28-438e-8fa9	Unhealthy-f	Today, 09:58:57		-0.04	100%	1 Unhealthy-fun	el.	1	
Retrain model	0	0c8432e0-0484-470c-a774	Unhealthy-f	Today. 09:58:57						I	1
Live classification	0	1a899717.5445.4d2b.803	Unhealthy-f	Today 09:58:56	2					1	
		the set of	and a second second second								

FIG 4.7 TESTING MODEL

EDGE IMPULSE	DEPLOYMENT (BALX007-PROJECT-1)		🕖 balakrishnan
Dashboard	Deploy your impulse	Build output	
Devices		417680)	
Data acquisition			
Impulse design		ter	
Create impulse			
• image	Built C++ library		
Transfer learning	📽 Learn how to integrate this library		
Anomaly detection	C++ library Arduno library WebAssembly	Creating archive	
Retrain model		Creating archive OK	
Line discription in	Build firmware	Job completed	

FIG 4.8 DEPLOYING C++ LIBRARY

4.4 PREDICTION





FIG 4.9 PREDICTION-HEALTHY LEAF

FIG 4.10 PREDICTION UNHEALTHY LEAF

5.CONCLUSION

Thus this system provides a simple way of detecting the plant health status. This project is developed considering simple design and providing cost effective solution for farmers. This system is more reliable and efficient since the model is trained using abundant data and can be improved when more data is collected to train the model.

6.FUTURE SCOPE:

After having implemented this model for determining plant health, there remains scope for improvements. This system can be integrated with drone technology for "precision agriculture" application. The data collected can be used for higher order analytics and research. This project can also be used to determine nutrient deficiency in plants when trained with more precise data set.

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